International Trade, Learning, and Firms' Heterogeneous Performance: Theory and Evidence from Developing Economies

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Chapter 1

Introduction

Do firms in developing countries improve their performance through trading with developed countries? How can firms in developing countries learn the advanced foreign technology through international trade? Who exports what? These questions have been motivating studies through macro-, meso- and recently micro-level analysis. This thesis investigates those questions at the micro-level both theoretically and empirically. It aims at understanding firms' heterogeneous performance in learning as they adjust to the international trade. Special attention is given to firms in emerging China as well as Central Asian and Eastern European economies.

1.1 Micro-foundations on International Trade and Learning

Both the "new" new trade theory and the Neo-Schumpeterian theory emphasize the importance of firm heterogeneity in understanding the economic performance because trade and learning is primarily a firm-level effort.

Inspired by the micro-level empirical findings that only a small proportion of firms export and exporters systematically differ from nonexporters, the "new" new trade theory relates the heterogeneous export decision of firms to their productivity differences (Melitz, 2003; Eaton and Kortum, 2002; Ghironi and Melitz, 2005, 2007). Incorporating firm heterogeneity in productivity based on Hopenhayn (1992) theory into Krugman's (1979) monopolistic competition trade model, the seminal work by Melitz (2003) proposes that the presence of fixed entry cost partitions more productive firms entering the international market under a fractional trade while the least productive firms exit and less productive firms only serve the domestic market. This explains the inter-industry trade pattern observed from empirical studies, in contrast to conventional trade theories' arguments about the complete specialization and comparative advantages in the industrial level, such as Ricardo or Heckscher-Olin theory. Market selection reallocates resources toward more productive firms within industries. The aggregate level of productivity will rise in response to trade because low-productivity firms diminish and exit, and high-productivity firms expand through penetrating the export market successfully.

The theory leads to the substantial investigations of two interwoven arguments of "self-selection" and "learning-by-exporting" at the firm level. The former argues that only more productive firms enter the foreign market, meanwhile, the latter states that the exposure to international market causes an improvement of productivity for exporters, although this post-exporting effect is less robust among the empirical findings. These two arguments essentially correspond to two functions of trade: (1) altering the allocation of resources in an economy; (2) transmitting the knowledge internationally. The improvement of aggregate productivity through exporting predicted in Melitz (2003), however, is not connected to the knowledge acquisition by firms. It is simply due to an inward shift of the demand curve caused by the entry of foreign competitors rather than due to the generation of new technology.

Instead of considering learning a by-product of exporting, recent studies have paid more attention to the interaction between exporting and other productivity-enhancing decision, which is typically investment in technology (Costantini and Melitz, 2007; Aw et al., 2008; Mayneris, 2010). The model of Melitz (2003) is then extended to incorporate the decision of firms to upgrade technology (Bustos, 2011), or to decrease the cost and develop new product mix (Atkeson and Burstein, 2010), or to invest in R&D (Aw et al., 2008; Lileeva and Trefler, 2010). Treating investment in technology as an additional fixed cost to raise firm productivity, Lileeva and Trefler (2010) and Bustos (2011) demonstrate that exporting induces firms to invest in technology because the presence of a larger market through exporting can spread out the fixed costs required by R&D investment, and thus make these investments more profitable. Consequently, the expectation of penetrating the international market evokes firms to innovate Costantini and Melitz (2007). The subsequent improvement in productivity achieved through investing in R&D conversely lead to the export decision of firms. The potential learning though exporting only happens to firms that invest in R&D or upgrade their technology (Lileeva and Trefler, 2010)

Learning, however, is “cumulative and local”, according to the Neo-Schumpeterian theory. Departing from the canonical theories, the Neo-Schumpeterian theory concerns firm heterogeneity and the learning behaviors at its root (Nelson and Winter, 1982). The source of firm heterogeneity stems from their bounded rationality which results in a routinized “rule of thumb” strategy in R&D investment, and uncertainty of innovation. Firm learning, typically technological learning, is understood as a continuous process and depends on their present techniques in use and their investment efforts (Dosi and Orsenigo, 1995; Silverberg and Verspagen, 1994). Hence, learning is heterogeneous across firms and path dependent.

The interaction between exporting and learning is explored through integrating the Kaldor-Verdoorn’s cumulative causation or the post-Keyensian growth theory into the micro-dynamic mechanism proposed by Nelson and Winter’s (1982) pioneering work (Dosi et al., 1994; Silverberg and Verspagen, 1994, 1995; Lorentz, 2004). Successful learning in the Nelson-Winter type of firms, modeled as the realization of imitation, is proportional to the technological searching zone, the R&D level of firms, and their absorptive capacity from spillovers of other firms' R&D. The relationship between the technological gap and the learning outcome is usually assumed to be inverted U-shaped (Cantner and Pyka, 1998). Although exports enlarge the searching zone of firms, successful learning in the international market is more difficult than in the domestic market due to the geographic boundary of knowledge spillovers, which is captured by a geographic distance parameter in the model. Meanwhile, export demands determine the magnitude and the multiplier effect of investment and output, hence they bear on the autonomous growth of firms and bring the increasing returns for investment. Innovation and learning improve firm productivity. A country's comparative advantage is therefore the *ex post* outcome of innovation, learning, and selection at the firm level.

Technological learning from Neo-Schumpeterian point of view is demonstrated not only in firm productivity, but also in a more comprehensive framework, that is, "technological capabilities".

1.2 Technological Capabilities and Channels of Learning for Firms in Developing Economies

Technological capabilities refer to firms' ability to master the technology, explore it and create new technological knowledge (Lall, 1998). It is an intrinsically multi-dimensional concept, including production, investment, and innovation capabilities. These correspond to the ability to maintain and operate the production facilities, the ability to expand capacity and establish new production facilities, and the ability to create new technology and commercialization respectively (Kim, 1997). Building technological capabilities involves not only the formalized R&D, but also the commercialization of the technology and its customization to the local market. This analytical framework has been widely used to understand how latecomer firms in developing economies, such as Korea and Taiwan in the 1980s and the 1990s, successfully caught up and learnt the advanced technology from developed economies while their counterparts in African countries failed to do so (Kim, 1997; Bell and Pavitt, 1993; Ernst and Kim, 2002; Hobday, 1995; Lall, 1998).

1.2.1 Dynamics of technological capabilities

From the resource-based view, the acquisition of technological capabilities by firms can be considered a result of the interaction between internal resources and external resources (Teece et al., 1997). With respect to the situation of firms in developing economies, the latter is generally the advanced foreign sources of technology. Based on a survey from case studies on a number of firms, Lall (1992) documents three identified stages along the dynamics of technological capabilities. Firms with the experience-based level of capabilities mainly do simple and routine tasks. Next comes search-based capabilities: firms at this stage undertake adaptive and duplicative tasks. They replicate the production and design from external sources either in order to customize it to the local market or to achieve a more efficient usage through a better understanding of the advanced technology. Successful accumulation of search-based capabilities leads firms to reach the research-based level of capabilities. Firms at this advanced level are capable of implementing innovative and risky tasks. They set up complete production systems, and design new processes and products, all of which ultimately set a stage for basic or potentially frontier R&D activities.

1.2.2 Learning from various channels

Different channels of foreign technology are observed to contribute to the transition of firms in terms of technological capabilities, which can be (1) transmission of ideas independent of goods, such as patent licenses and FDI; (2) trading in intermediate and capital goods that embody technology. Each option offers unique advantages and disadvantages and plays a different role in firm learning at various stages.

It is argued that direct sources of foreign technology are more important for the early phase of accumulation. Imported intermediate inputs, embodying the advanced technology from their foreign origin, improve the production process of firms directly. Investment in machinery and equipment is observed to have a strong impact on total factor productivity and the growth of importing firms (De Long and Summers, 1991; Almeida and Fernandes, 2008; Acharya and Keller, 2009). Patent licenses facilitate the introduction of new technology or products which are already established or readily available in firms from developed economies. Successful implementation of licensed patents may require both tacit knowledge and skilled workers; hence it stimulates the learning process of firms. FDI may bring a new production set and new technology for firms that receive the direct investment, on the one hand. On the other hand, parent firms abroad will try to protect their advanced technology from diffusing to the local firms in order to prevent their monopoly positions from eroding (Saggi, 2002). Therefore, FDI is more likely to facilitate the acquisition of technological capabilities for firms at the early stage. Kim (1997) argues that technology licenses and turnkey were especially important for the initial accumulating process of catching-up by Samsung and Hyundai. Through original equipment manufacturing (OEM) and in-plant training, these firms develop their own strategy to absorb and implement the advanced foreign technology. However, once it is assimilated by firms, the foreign technology itself is not as important as in the initial stage. Firms start to compete on the international market after they develop their own capabilities.

Exporting contributes to the development of technological capabilities in an indirect way by allowing local reverse engineering and access to new machineries and equipments. Many latecomer economies adopt the export-oriented strategy to accelerate their development, such as Korea, Taiwan and Indonesia (Ernst et al., 1998). Exporters need certain level of capabilities and put forth additional effort to assimilate the indirect knowledge; consequently, exporting is supposed to encourage the transition of firms towards an advanced level of technological capabilities.

1.3 Stylized Facts and "Less" Stylized Facts on Trade and Learning

Following Kaldor's (1961) suggestion, I summarize the relevant empirical investigation and theoretical explanations on trade and learning in this section. Based on stylized facts and "less" stylized facts, I derive the research questions of this thesis.

1.3.1 Stylized facts

Stylized fact 1 *Exporters are systematically different from nonexporters. They are superior to nonexporters in terms of productivity measured by value-added per worker, capital intensity, size, employment, wages, and labor quality.*

Bernard and Jensen (1999) originally document that just four percent of U.S. firms are exporters and that the top 10 percent of those account for 96 percent of all the nations exports. Exporters are systematically different from nonexporters. With more firm-level data available, a series of empirical studies confirms the small proportion of exporters within industries and the systematically superior performance of exporters to nonexporters in Columbia, Germany, Korea, Mexico, Morocco, Slovenia, Taiwan, the UK and the US. These studies identify the difference by estimating the exporter premia. It is the coefficient of the export dummy in a regression of labor productivity or firm other characteristics, such as average wages or capital intensity, on a set of control variables. Table 1.1 summarizes representative findings regarding this stylized fact. Note that the proportion of firms engaged in exporting in the US reached to 18 percent in 2002.

Table 1.1: Stylized Facts on Exporter Premia and Self-selection

Economy	Exp%	Productivity	Wage	Capital	Period	Sample	Author
Columbia	13	0.43***	0.17***	0.49***	1981-1991	6,454	Isgut (2001)
Germany	44	0.21**	0.017	0.12**	1978-1992	7,624	Bernard and Wagner (1997, 2001)
Korea	29	0.39***	0.13***	0.40***	1990-1998	88,864	Hahn (2004)
Slovenia	46	0.30***	0.16***	0.37***	1994-2000	6,391	De Loecker (2007)
Taiwan	38	0.049***	0.054***	-	1981-1991	10,000	Aw et al. (2000, 2001)
UK	35	0.076***	0.044***	0.25***	1988-1999	8,992	Girma et al. (2004); Greenaway and Yu (2004)
US	18	0.26***	0.17***	0.32***	2002	60,000	Bernard et al. (2007a)

*Notes: significance levels: ***$p < 0.01$ ** $p < 0.05$ * $p < 0.1$. "Exp%" denotes the percentage of exporters among samples. "Wage" and "Capital" refer to the average wage and capital per worker. The result from Taiwan (China) is re-aggregated from five industries by the author.*

Stylized fact 2 *More productive firms select themselves to the export market.*

The self-selectivity into export is confirmed by almost all established studies for firms in economies listed in Table 1.1 using the Probit regression. This fact is explained successfully with the fixed entry cost under a frictional trade by Melitz (2003). Wagner's (2007) survey documents the self-selectivity of exporters for more economies.

Stylized fact 3 *Technology mastery is not free and learning requires deliberate efforts by firms. Productivity and R&D investment across firms are positively related.*

Studies on the catching-up of latecomer firms reveal that the tacit aspect of knowledge embodied in the advanced technology requires a certain level of absorptive capacity of firms and the amount of their deliberate efforts

(Bell and Pavitt, 1993). These efforts involve trial and error, accompanying substantial R&D investment. The role of R&D investment among latecomer firms is to improve the ability to absorb the existing technology, rather than innovating at the knowledge frontier (Cohen and Levinthal, 1989; Kim, 1997). Firms are significantly different in their willingness to undertake and succeed in these tasks. This can be seen from highly persistent differences of R&D intensity across firms. The positive relationship between productivity and R&D investment has been found in firm-level analyses among a vast number of studies for China, Japan, Korea, Taiwan, the US, and other OECD countries (Griliches, 1998). Neoclassical growth theories are criticized for their ignorance of costly technological learning in the South, and accordingly the inability to explain firm heterogeneity in learning in the presence of equally advanced technology in the international market. For example, despite years of production, many firms in large-scale sectors in African countries failed in achieving technological progress (Bell and Pavitt, 1993).

1.3.2 "Less" stylized facts

The empirical testing on a number of hypotheses related to the trade and learning is quite mixed. These inconclusive results either call for an alternative theory or for further empirical investigations.

Learning by exporting. The hypothesis that exporting leads to a higher level of productivity does not find robust results from empirical studies. Most economies listed in Table 1.1 do not support the evidence of learning-by-exporting, except for Slovenia. De Loecker (2007) documents a higher productivity through exporting for firms in Slovenia by comparing the difference of productivity trajectories between exporters and their matched domestic counterparts. Other supportive evidence is reported from firms in sub-Saharan African economies and Canada (Trefler, 2004; Van Biesebroeck, 2005). The international study group on exports and productivity (2007) compares the evidence of learning-by-exporting effect across 14 countries, and only observe a positive effect for Italy. The systematic difference between exporters and nonexporters is mainly interpreted as self-selecting rather than learning-by-exporting.

These mixed results are first consider to be a country-specific effect: developing economies are supposed to benefit more from exporting through the broader access to more advanced technology in the presence of trade (Castellani, 2002). However, with respect to patterns in the post-export performance of firms, the evidence does not present a systematic difference between developed economies and developing economies. The importance of the interaction between exporting and investment in technology has been emphasized recently for firms in some economies, such as Argentina, Canada, Taiwan and the UK (Bustos, 2011; Lileeva and Trefler, 2010; Aw et al., 2008; Harris and Li, 2009). The post-export productivity boost is observed for exporters that invest in technology. For example, treating the Canadian-US Free Trade Agreement as a quasi-experiment, Lileeva and Trefler (2010) document that Canadian exporters improve their labor productivity through exporting and that exporters with lower initial productivity have a greater gain through investing in R&D.

Another stream of studies concerns the variation in post-export performance of firms across industries. Aw et al. (2000) observe the productivity improvement for Taiwanese firms in the textile and apparel industries after commencing export, but not for firms in plastics, electronics or transportation. Most existing theoretical models, following Melitz's (2003) seminal work, assume labor to be the only production factor. This assumption of single-factor, together with a symmetric-country structure conceals the effect of a sector's peculiarities on the export decision of firms, and on their subsequent learning. Factor intensity and endowments are then incorporated into the heterogeneous-firm model by Bernard et al. (2007b). This two-factor-two-sector model relates the comparative advantages with the performance of firms. It predicts that an aggregate productivity boost caused by the expansion of more productive firms in response to trade is stronger in comparative advantage sectors.

Leontief paradox. The Heckscher-Ohlin theory predicts that trade patterns are based on a country's relative endowments in the factors of production, such as capital or labor. Leontief (1958) finds that the US – the most capital-abundant country in the world – exported labor-intensive goods and imported capital-intensive goods, in contrary to the prediction of the H-O model. This so-called "Leontief paradox" casts doubts on the effect of factor endowments on trading, and leads to the criticism of the H-O theory for its assumption on the immobility of factors and for its static features. It also inspires more empirical studies on H-O theory for more economies. These tests produce mixed results.

Some economies provide the supportive evidence for H-O theory, such as India, East Germany, and the US-Japan trade (Stolper and Roskamp, 1961; Tatemoto and Ichimura, 1959). Among other explanations for the paradox, Keesing (1965) argues that the US has more highly-skilled workers than capital by differentiating skilled workers from unskilled workers. Labor-intensive goods in the US can be understood as human capital-intensive or skilled worker-intensive, and not particularly intensive in unskilled labor. Recently, Bernard and Wagner (2001) have documented that more than a third of the US companies in certain capital- and skill-intensive industries – computer, electronic and electrical equipment manufacturing, and chemical manufacturing – are exporters. These findings suggest that factor endowments proposed by H-O theory may be still at work with trading: who exports what to whom hinges on factor abundance, i.e. the presence or lack of capital, skilled labor, cheap labor, or natural resources (Bernard et al., 2010).

Nevertheless, it has been argued that technology differences play a major role in explaining a country's trade performance beyond factor endowments (Nelson and Norman, 1977; Bell and Pavitt, 1995; Grossman and Helpman, 1995). The surpassing of the UK by the US and Germany in the middle to the late nineteenth century, and the booming of Japan since the 1970s were accompanied by substantial investment and success in technology improvement (Nelson, 1990; Dosi et al., 1990). Table 1.2 presents the technological difference among the world's top exporters and the Asian tigers in 2007 using the number of patents registered in the US Patent and Trademark Office (USPTO) as an indicator for a country's technological performance. Except for China, all top exporters possess a large share of patents, especially the US, Japan and Germany. Japan has been the major foreign country patenting in the US since the 1970s. Taiwan and Korea has experienced solid increases in the patenting activities at the USPTO with their emerging in the international market.

While technology *per se* is not considered an endowed factor of a country, the generation of technology and technological learning are not independent of endowed factors, such as capital or labor. The acquisition of technological capabilities corresponds to the heavy investment in purchasing machineries, upgrading production lines, or training workers at the initial stage of development. Nelson and Pack (1999) describe the catching-up process in East Asian economies as proceeding from capital accumulation to technological assimilation, as a dispute to Krugman's (1994) argument that the Asian's miracle is simply capital accumulation through physical investment.

As the second largest exporter in 2007, China owned only 0.67 percent of patents with foreign origins between 2000 and 2007, although the share has been increasing since late 20^{th} century. This suggests that factor endowments may be at work when explaining the trade patterns of China, and Chinese firms are still in the early stage of technological learning.

Transition of firms in terms of technological capabilities. The path of technological learning, moving through identifiable stages towards the acquisition of technological capabilities, is observed for representative firms in automobile, electronics, chemical, and machinery industries in Korea, Taiwan and Japan from the early 1960s through the 1990s (Kim, 1997; Kim and Nelson, 2000; Dahlman et al., 1987; Lee and Lim, 2001). Those analyses provide guidelines for both firm-level strategies and government

Table 1.2: Patenting in the US by Top Exporters and the Asian Tigers

Economy	Number of Grant Patents 1977 - 2007	Number of Grant Patents 2000 - 2007	% Foreign Patents 1977 - 2007	% Foreign Patents 2000 - 2007	Export Rank 2007
China	5,348	4,607	0.33	0.67	2
Germany	251,597	88,658	15.39	12.92	1
US	2,004,054	764,051	122.59	111.38	3
Japan	682,050	285,617	41.72	41.64	4
France	95,584	31,544	5.85	4.60	5
Italy	42,209	15,201	2.58	2.22	6
Netherlands	32,699	12,135	2.00	1.77	7
UK	95,917	32,514	5.87	4.74	8
Asian Tigers					
S. Korea	54,036	38,411	3.31	5.60	10
Hong Kong	8,558	5,185	0.52	0.76	12
Singapore	4,016	3,209	0.25	0.47	14
Taiwan	79,019	54,368	4.83	7.93	17
Foreign Origin	1,634,758	685,974	100.00	100.00	-
Total	3,638,812	1,450,025	211.38	222.59	-

Source: Calculated according to the data from the US Patent and Trademark Office and WTO report.

policies. However, the theory of the accumulation of technological capabilities has normally been analyzed utilizing case studies, focusing on large firms in either one single industry or country (Fagerberg et al., 2009). Few studies examine the development of technological capabilities throughout the experience-based to the research-based level for a large number of firms. The difficulty lies in lacking of an appropriate indicator or approach to capture technological capabilities owing to the fact that the concept of "capability" incorporates multi-dimensional factors in production, investment, and innovation, all of which must be combined in such a way to provide a comprehensive yet measurable structure in order to implement the econometric analysis. The existing empirical studies adopt either a single indicator to measure technological capabilities for firms, such as R&D investment or on-job training (Aw and Batra, 1998), the number of patents (Motohashi, 2008), or an aggregate index calculated through an arbitrary combination (e.g., average) of different determinants (Archibugi and Coco, 2004). The latter is also applied to evaluate the technological capabilities at the country level by UNCAD. None of approaches are capable of capturing the comprehensive implicitness of technological capabilities, nor of identifying the transitions of firms. Moreover, firms in Eastern European and Central Asian economies are often absent from this area of analysis.

1.3.3 Research questions

Based on the above analysis, this thesis investigates three groups of questions:

1. Do Chinese firms generate higher productivity through exporting? Why or why not?

2. Does the decision to export induce firms to invest in R&D and vice versa in China? Do exporting and R&D investment complement on improving the performance of Chinese firms?

3. Can the dynamics of technological capabilities be identified for a large group of firms? How do different channels of foreign technology impact the transition of firms in Central Asian and Eastern European Economies?

From an empirical point of view, China is a particularly interesting emerging economy to study because of its large gross economic capacity and its special transitional market mechanism. Moreover, the end of the 20^{th} century witnessed China open more to the world, which led to a substantial boost in exports and growth. China's export-GDP ratio has arisen from 18 to 36.5 percent since 2000, accompanying a dramatical increase in the number of export entrants. In 2009, China overtook Germany as the world's largest exporter, while the ratio of R&D expenditures to GDP was only 1.5 percent. The controversy among scholars and policy-makers on the impact of exporting on the performance of firms is still unresolved. It is still unclear whether the trade liberalization accelerates firms to upgrade technology or reinforces the comparative advantages towards resource-oriented or labor-intensive sectors.

1.4 Overview and Main Contributions

Chapter 2, 3 and 4 are designed to analyze and answer the above research questions. Each chapter is a separate article, but they are logically connected and altogether encompass the big picture of the trade and firms' learning in developing economies. The thesis combines both Neo-Schumpeterian theory and the "new" new trade theory. It follows the logic of "empirical analysis – theoretical model – empirical analysis". Firm heterogeneity in exporting and learning is the focus of the whole thesis, however, the analysis goes through the meso-level, macro-level and back to the micro-level for reasoning. The design of the structure and the methodology are shown in Figure 1.1 and explained in more detail in Section 1.4.1.

1.4.1 Roadmap and methodology

Chapter 2 starts with the empirical analysis on whether exporting leads to a higher level of productivity for Chinese firms. It adopts the combination of propensity score matching and difference-in-difference estimation to disentangle the selection effect, which can be either positive or negative, from the learning-by-exporting effect. The evidence does not show that Chinese firms generate significant increases in productivity through participating the export market. This result holds for both the whole sample and the separate industries. However, in order to penetrate the international market, firms conduct more product innovation when foreign sales are initiated. This effort does not continue once firms start exporting.

The reason why exporters fail to improve their productivity is explored tentatively. On the one hand, labor dominates the expansion of exporters.

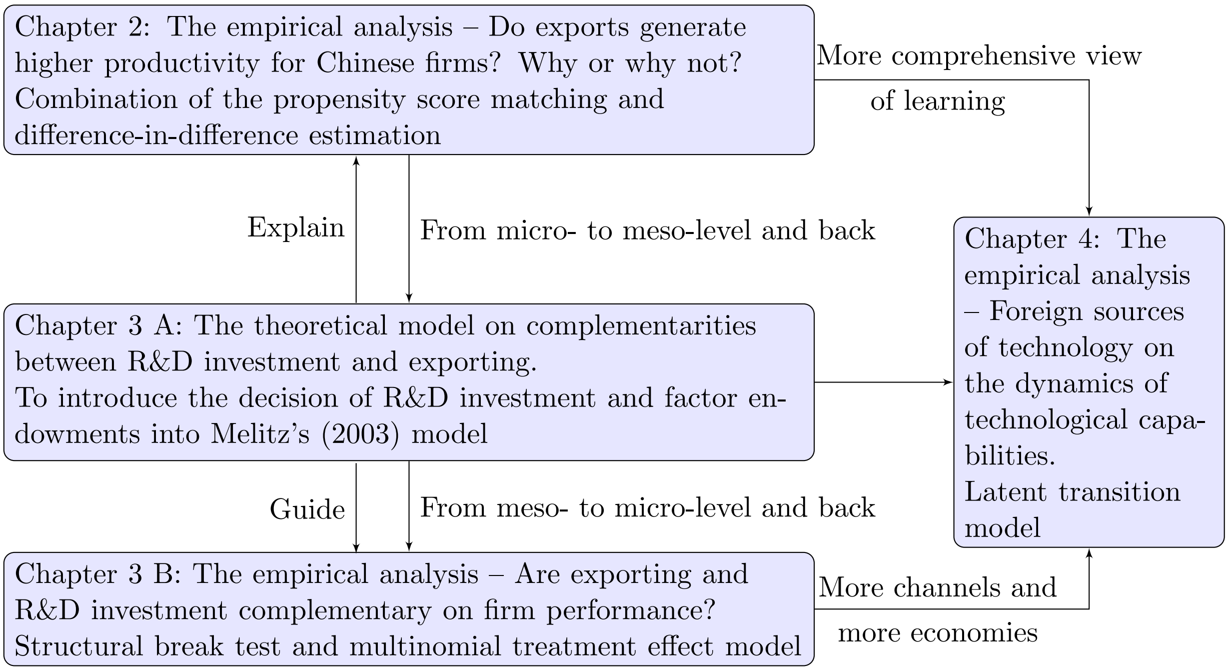


Figure 1.1: Roadmap and Methodology

Compared to the matched non-exporters, exporters experience the faster changes in labor than in value-added and capital, especially for exporters in labor-intensive sectors. Exporters tend to hire more employees per value-added, per capital and per sales than non-exporters, implying that the export-oriented strategy may generate more jobs but not necessarily improve the efficiency of firms. On the other hand, exporters fall short of R&D investment needed to enhance the productivity through the export participation because the deliberate efforts by firms are required in order to absorb the advanced technology available in the international market. The combination of exporting and conducting R&D positively correlates with the productivity of firms. The presence of R&D investment shows a significantly positive effect on the productivity for both exporters and non-exporters, while the positive effect for exporters is larger than for non-exporters. Moreover, the prominent usage of labor by exporters results in a lower level of productivity than that of non-exporters in the labor-intensive sectors. This finding is neither consistent with the established theories, typically the model of Melitz

(2003) which predicts that more productive firms enter the export market, nor with the stylized facts described in section 1.3.1. Consequently, these results suggest that lower labor costs may still serve as a fundamental factor in supporting the exports of Chinese firms.

In conjunction with chapter 2, chapter 3 analyzes the complementary relationship between the decision to export and invest in R&D for Chinese firms in more detail. Two kinds of complementarity between exporting and R&D investment are analyzed: first, the positive effect of either decision on the tendency of firms to adopt the other one; second, the complementing effect of the two decisions on improving firm performance.

Chapter 3 starts with the descriptive analysis on patterns of the decision of Chinese firms to export and its interaction with investing in R&D. This chapter documents a systematic difference between labor-intensive and capital-intensive sectors regarding on the productivity of firms and their decisions in China. First, less productive firms tend to enter the international market in labor-intensive sectors, while the situation is reversed in capital-intensive sectors. Second, firms that start R&D activities are more productive than the sectoral average level. This holds for all sectors, however, when differentiating exporters and non-exporters, exporting firms that start to conduct R&D are less productive than their non-exporting counterparts in the same sector, except for highly capital-intensive sectors, such as tobacco and petroleum exploration. Third, the fraction of R&D investors is higher among exporters than non-exporters. Fourth, compared to other firms, exporting firms that engage in R&D activities demonstrate the highest profits. These findings jointly suggest a complementary relationship between the exporting decision and the R&D investment decision.

In order to guide the empirical analysis in this chapter, I develop a theoretical model by incorporating the R&D decision of firms and a country's factor endowments into the model of Melitz (2003). It then extends Melitz (2003) model to a scenario of two-country-two-sector-two-factor. This modification emphasizes the importance of a sector's peculiarities in understanding the exporting behavior of Chinese firms and the influence of deliberate efforts by firms on the outcome of learning. The model predicts that exporters are not necessarily more productive in relatively factor-abundant sectors or comparative advantage sectors. In theory, the productivity threshold for exporting may be lower than local survival threshold in factor-abundant sectors where the productivity threshold for R&D investment is higher than the productivity threshold for exporting. Therefore, in those sectors, less productive firms export while more productive firms invest in R&D to achieve a higher domestic market share. Furthermore, more productive firms select themselves to conduct R&D in all sectors; though exporting lowers the threshold of R&D investment when firms are assumed to make their decisions in two steps. The effect is more obvious in comparative advantage sectors. This positive linkage between the decision to export and invest in R&D occurs because the larger market share through exporting compensates the fixed cost required by R&D investment. Moreover, utilizing the supermodularity theory, I demonstrate that the presence of exporting and R&D investment are complementary on improving the profitability of firms.

The decision of Chinese firms to export or conduct R&D are estimated separately using a Probit regression. The structural break test confirms different patterns in firms' entry to the export market between labor-intensive and capital-intensive sectors. In labor-intensive sectors, less productive firms tend to export, while in capital-intensive sectors, the productivity has no significantly impact on the decision of firms to enter the export market. In both cases, the presence of R&D investment shows a positive effect on the probability of firms to export. Furthermore, more productive firms select themselves to conduct R&D activities. This result holds for all sectors. The exporting status increases the probability of firms to conduct R&D. Besides, the interaction term of export and productivity shows a significantly negative sign in the regression on the decision of firms to start R&D, which implies the exporting experience lowers the productivity threshold for firms to start R&D. Hence, a bidirectional feedback relationship exists between the exporting and R&D investment decision of firms. The multinomial treatment effect model is applied to identify the complementing effect of R&D investment and exporting on improving the productivity of firms. The self-selection bias caused by various decisions of firms is corrected through a mixed multinomial logistic regression.

In chapter 4, the analysis moves to a more comprehensive measure of learning and considers various channels for firms in more economies. In addition to exporting, FDI, technology licenses and imported intermediate inputs are incorporated into the analysis as channels for firms in developing economies to learn the foreign technology. I propose a latent transition model to estimate simultaneously whether firms belong to the same category of technological capabilities and the probability of their transitioning among various levels. This approach does not assume any pre-determined cluster structure. The technological capabilities of firms are modeled as latent states which cannot be observed directly but are detectable from firms performance in measures of production, investment and innovation. By doing so, it is possible to examine and generalize arguments from case studies for a large number of firms in Eastern European and Central Asian economies. This approach distinguishes this chapter from previous studies. The determinants of the transitions of firms in terms of technological capabilities are estimated using a multinomial logistic regression by including different channels of foreign technology.

The estimated latent transition model identifies three sequential development stages for sample firms, which confirms the arguments from previous case studies about the dynamic patterns of firm learning: firms develop their technological capabilities through a set of definable stages from the experience-based, to the search-based, and then to the research-based level. The comparison analysis on a number of Eastern European and Central Asian economies suggests that Slovenia and Croatia have more advanced level of technological capabilities because they have the largest share of firms that possess the research-based level of capabilities, while Azerbaijan and Uzbekistan perform the worst owing to the fact that most firms in these countries load in the experience-based level. Moreover, the transition analysis on technological capabilities reveals that firms tend to stay in their current stage, therefore they need to exert the additional effort in order to improve their technological capabilities.

Direct sources of technology are more important for the transition of firms in terms of technological capabilities, especially for firms at the lower levels. More specifically, the usage of technology licenses encourages the transitions of firms at all stages of technological capabilities towards more advanced levels. Imported intermediate inputs play a significant role in keeping firms at the intermediate level of technological capabilities and transitioning of firms towards the advanced level. FDI is observed to have important influences on the transition probability for those firms which only have basic technological capabilities. However, the exporting intensity does not show a significant effect on the transitioning of firms along different levels of technological capabilities.

To summarize, the analysis starts from the empirical analysis and documents some stylized and "less" stylized facts for Chinese firms. The seemingly unusual evidence, especially the systematic difference between exporters and non-exporters between labor- and capital-intensive sectors, calls for a new theoretical model in chapter 3. The extended model analyzes heterogeneous decisions of firms to export and invest in R&D under the scenario of factor endowments. By doing so, it brings the micro-level analysis to the meso-level with respect to a country's comparative advantages. It then goes back to the firm-level empirical analysis using the structural break test and multinomial treatment effect model to analyze the experience of Chinese firms. The analysis further moves to the macro-level when the dynamics of technological capabilities is identified and compared for firms in Eastern European and Central Asian economies in chapter 4. The last chapter summarizes the main research findings and proposes some policy implications, as well as possible future research.

1.4.2 Data

Two main datasets are used in the thesis. The first source of data is the Annual Survey of Chinese Enterprises (ASCE) for the period of 2000 and 2007. Collected and maintained by National Bureau of Statistics, China, the ASCE covers all state-owned firms and non-state-owned firms with at least five-million RMB in annual sales from manufacturing sectors, identified at the 4-digit industrial level.[1] These firms are defined as "large-and-medium-size enterprises" in China. They account for around 25 percent of all registered firms, around 70 percent of total export value, and over 50 percent of total R&D expenditures in China for each year. The survey provides detailed information about the financial performance of firms through variables such as identification, assets, liabilities, capital structure, sales, employment, value of new product, and export value, each of which is available for approximately 160,000 to 336,000 firms each year. This dataset is used in chapter 2 and 3.

The second data source is the Business Environment and Enterprise Performance Survey (BEEP), collected jointly by the European Bank for Reconstruction and Development and the World Bank. The data covers 23,570 firms with at least five full-time employees from 27 Eastern European and Central Asian economies between 2002 and 2009 over intervals of three to four years. The survey provides detailed information about firm characteristics, economic performance, innovation, investment environment and degree of competition. These samples are designed to have a representative picture of industries for each economy. They cover both manufacturing and service sectors, identified at the 4-digit ISIC industrial level. This dataset is used in chapter 4.

In addition, the thesis refers to the USPTO data (1965 to 2010) and WTO report (2000 to 2008) for the supplementary information.

[1] Data during 2005 through 2007 covers firms in three service sectors, but they are included in the survey simply because they were classified as manufacturing firms before 2005. I therefore restrict the analysis to manufacturing sectors in order to keep the classification consistent.

1.4.3 Contributions

This thesis enriches the micro-level evidence on trade and learning process by analyzing a large sample of Chinese manufacturing firms and firms in Eastern European and Central Asian economies. First, it offers a better understanding in China's comparative advantage and competitive advantage in the international market by identifying cheap labor as an important factor in supporting the expansion of Chinese exporters. Evidence does not show firms reach higher productivity through exporting in China. Exporters are observed less productive than non-exporters in labor-intensive sectors. Second, It helps to understand how the export decision of Chinese firms interacts with their decision to invest in R&D, and how the comparative advantages relate to, and are influenced by the two decisions. The thesis documents the evidence of a complementarity between R&D investment and exporting in improving the productivity of Chinese firms. Export market participation induces firms to conduct R&D and vice versa. Third, a latent transition model is originally introduced to identify the dynamics of technological capabilities for a large group of firms. Through this approach, it is possible to generalize arguments from previous case studies on the transitioning of firms along the definable stages of technological capabilities. These findings then shed light on how latecomer firms in developing countries respond to trade liberalization and take advantage of foreign sources of technology.

The thesis contributes to micro-founded theoretical models by extending the model of Melitz (2003) to two production factors and incorporating the decision of firms to conduct R&D. The extended model explains the systematically different patterns regarding the performance of Chinese exporters and their decision to invest in R&D between labor- and capital-intensive sectors. It also demonstrates the self-selectivity by more productive firms to invest in R&D and predicts the complementing effect of the two decisions on the profitability of firms. The model connects the micro-evidence to the meso-level performance in terms of a country's comparative advantage.

Moreover, the thesis provides some guidelines for the controversial RMB exchange rate policy and technology policy in developing economies.

1.5 Declaration of Co-authorship

Chapter 2 is based on a joint paper with Zhaoyuan Xu, "More Exporting, Less Efficiency? – Why Chinese Exporters Are Not Generating Higher Productivity". Zhaoyuan Xu and I contributed equally to the completion of this paper. Chapter 3 and 4 are based on two of my single-authored papers, "Complementarities between R&D Investment and Exporting: Theory and Evidence from Chinese Manufacturing Firms" and "Foreign Sources of Technology on the Dynamics of Technological Capabilities: Evidence from Firms in Developing Economies".

Chapter 2

More Exporting, Less Efficiency?–Why Chinese Exporters Are Not Generating Higher Productivity

This chapter examines whether exporting leads to higher productivity for Chinese exporters. In addition, it explores why learning does or does not occur among certain exporters. In its explanation of the heterogeneous decisions of firms to export and the co-existence of exporters and non-exporters within one industry, the "new" new trade theory argues that firms which perform better select themselves into the international market (Melitz, 2003). Conversely, the exposure to the international market results in a higher level of productivity for exporting firms compared to their domestic-oriented counterparts (Clerides et al., 1998).

Learning-by-exporting has been considered a driving factor for improving firms efficiency, especially for firms in developing economies. Competition on the international market allows them to access more knowledge about new production methods, inputs and product designs from their international partners. However, learning does not happen freely. Successful learning requires firms to develop their own strategy and put forth their efforts (Kim and Nelson, 2000; Kim, 1997). According to the Neo-Schumpeterian theory, learning is "local and cumulative" because it is more likely to build upon past experiences of production, and therefore learning is heterogenous across firms (Nelson and Winter, 1982; Dosi and Orsenigo, 1995).

Bringing the "new" new trade theory and the Neo-Schumpeterian theory together, this chapter investigates: (1) whether Chinese exporters generate higher productivity through exporting, and (2) why learning does or does not occur for some exporters.

From an empirical point of view, China is a particularly interesting emerging economy to study because of its large gross economic capacity and its special transitional market mechanism. Furthermore, the end of 20^{th} century witnessed China open up more to the world, and this led to a substantial boost in exports and growth. China's export-GDP ratio has risen from 18 to 36.5 percent since 2000, accompanying a dramatical increase in the number of export entrants. In 2009, China overtook Germany as the world's largest exporter. The controversy among scholars and policy-makers on the impact of exporting on the performance of firms, however, remains unsolved. It is still unclear whether the trade liberalization accelerates firms to upgrade technology or reinforces the comparative advantages towards resource-oriented or labor-intensive sectors. This chapter aims to clarify the effect of trade on the Chinese economy through examining the learning-by-exporting hypothesis for a large sample of Chinese manufacturing firms, and exploring the forces which drive the learning process. It thus sheds light on understanding the way Chinese firms cope with the international competition.

The main results of this chapter can be summarized as follows. First, exporters in China do not show the significant evidence of productivity improvement. This result holds for both the whole sample and separate industries. However, exporters present a higher ratio of new product value to output when foreign sales are initiated. Second, two factors can explain the lack of evidence for learning through exporting: On the one hand, changes in labor dominates the expansion of exporters. Exporters tend to hire more employees per value-added, per capital and per sales than non-exporters, implying that exporting may generate more jobs but not necessarily improve the efficiency of firms. On the other hand, exporters fall short of investing in R&D to absorb the advanced technology available in the international market. The combination of exporting and conducting R&D is positively correlated with the productivity of firms. The presence of R&D investment shows a significantly positive effect on the productivity for both exporters and nonexporters, while the positive effect for exporters is larger than for non-exporters.

The rest of this chapter proceeds as follows. Section two contains a review of the theoretical and empirical literature. Section three describes the dataset and provides the preliminary analysis. Section four introduces the econometric models and the estimation strategy. Section five reports the estimation results and their corresponding interpretation as well as the robustness check. Section six analyzes forces that lead to those results. The final section summarizes the main findings of this chapter.

2.1 Learning and Exporting: an Overview

2.1.1 Theoretical background

Foreign market opportunities and international competition have important influences on the course of a firm's technological progress. The idea that firms learn by exporting refers to a causal linkage between the exporting experience of firms and their productivity level. This link may arise through improving the management skills, investment, and the technological learning, as demonstrated by the following three sorts of mechanism.

First, market selection reallocates resources toward more productive firms within industries (Ghironi and Melitz, 2005). Melitz's (2003) model does not state the source of higher productivity for exporters. The mechanism works through an inward shift of the demand curve which drives out the less productive firms and leads to the reallocation of resources towards more productive firms within the industry. Consequently, the aggregate level of productivity increases in response to trade liberalization.

Second, the intense competition in the international market may drive exporters to invest in more productive technology or to adopt best-practice production techniques (Bustos, 2011). This can be considered the reallocation of resources within firms. Costantini and Melitz (2008) demonstrate that the anticipation of trade liberalization induces firms to invest in new technology prior to entering the export market. From the resource-based view, exposure to richer sources of knowledge and technology that are otherwise unavailable in the domestic market provides exporters the unique advantages to enhance their productivity through the diverse knowledge inputs. For example, exporters can benefit from the technical expertise of their buyers or from design specifications of their suppliers in ways that allow firms to develop their competence base (RodrÌguez and RodrÌguez, 2005).

Third, exporting activity is an important component to support autonomous growth of firms based on Kaldor-Verdoorn's cumulative causation – export demands determine a multiplier effect on investment and output. An expansion of the export sector may cause specialisation in the production of export products, which increases the productivity and the level of skills in the export sector. This productivity change may conversely lead to expanded exports and to output growth. As a result, the export demands assist the growth of firms and bring the increasing returns for investment (Los and Verspagen, 2006; Lorentz, 2004).

2.1.2 Empirical evidence

The micro-level evidence on the learning-by-exporting hypothesis is quite mixed. The systematic differences in productivity between exporters and non-exporters are mainly explained by self-selection into the international market rather than by learning-by-exporting for most economies, such as the U.S., Colombia, Mexico, Morocco, Korea and Taiwan (Aw et al., 2000, 2001, 2007; Roberts and Tybout, 1997; Bernard and Jensen, 1999).

Nevertheless, firms in sub-Saharan African economies and in Slovenia provide the supportive evidence that exporting leads to higher productivity (Van Biesebroeck, 2005; De Loecker, 2007). The international study group on exports and productivity (2007) compares the performance of firms with respect to self-selection and the learning-by-exporting effects for 14 countries and finds that only Italy shows supportive evidence of the learning-by-exporting effect.

Few studies have tried to explore the source of this discrepancy. These mixed results are first considered a country-specific effect: developing economies are supposed to benefit more from exporting through the broader access to more advanced technology in the presence of trade (Castellani, 2002). However, evidence does not present a systematic difference between developed economies and developing economies with respect to patterns in the post-entry performance of exporters.

It is worth noting that the importance of the interaction between exporting and investment in technology has been emphasized recently for firms in some economies, such as Argentina, Canada and Taiwan (Bustos, 2011; Lileeva and Trefler, 2010; Aw et al., 2008). The post-export productivity boost is observed for exporters that invest in technology. Another stream of studies documents the increases in productivity of firms vary across industries after foreign sales are initiated. For example, Aw et al. (2000) observe the improvement of productivity for Taiwanese firms in the textile and apparel industries after commencing export, but not for firms in plastics, electronics or transportation. Roberts and Tybout (1997) and Greenaway and Kneller (2007) argue that the degree of the industry's exposure to the foreign market helps to explain the asymmetric growth of productivity for exporters across industries. Bernard et al. (2007b) demonstrate that the increases in average industry productivity are stronger in comparative advantage industries.

Combining the "new" new trade theory and the Neo-Schumpeterian point of view, this chapter takes a deeper step towards understanding the post-entry performance of Chinese exporters, highlighting both the influence of industry's variation and the firms efforts to learn. In order to capture the benefits of internationalization, exporters need to develop the specific investment and put effort into accumulating the knowledge through experience with foreign contexts.

2.2 Data

The data comes from the Annual Survey of Chinese Enterprises (ASCE) from 2000 through 2007. Collected and maintained by National Bureau of Statistics China, the ASCE covers all state-owned firms and other "large-and-medium-size enterprises", which are non-state-owned firms with at least five million RMB in annual sales from manufacturing sectors.[1] These firms account for around 25 percent of all registered firms and around 80 percent of China's total exports in each period. The survey provides detailed information about the financial performance of firms, such as the identification, assets, liabilities, capital structure, sales, value of new products, and the export values, each of which is available for approximately 160,000 and 336,000 firms across different years.

[1]Data from 2005 through 2007 covers firms in three service sectors, but they are included in the survey simply because they have been classified as manufacturing firms before 2003. We therefore restrict the analysis within manufacturing sectors in order to keep the classification consistent.

2.2.1 Data description

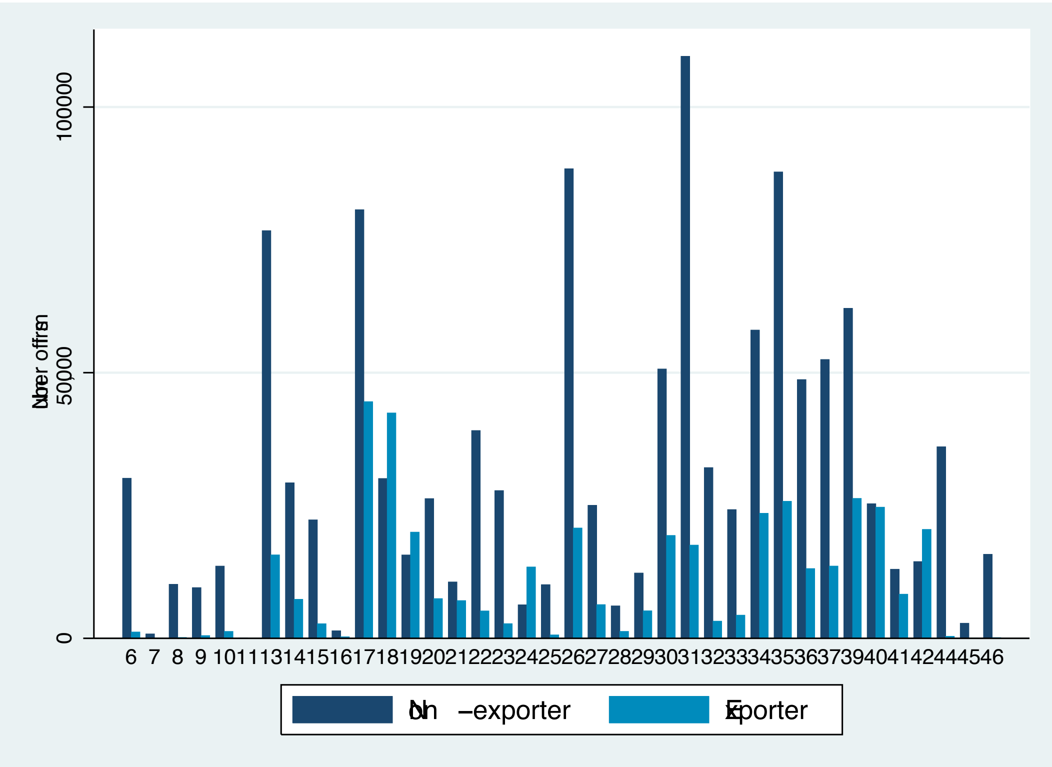
an unbalanced panel structure, the dataset can be used to derive the dynamics of firms' entry into or exit from the domestic market as well as the international markets (see Table 2.1 for more details). The data in 2004 is excluded from the following analysis because the discrepancy of the index system between the national economic survey in 2004 and other years makes it impossible to integrate all variables, especially because the firm-level export value is not available in 2004.

Table 2.1: Sample Size

Year	N. Firms	Export	Start	Quit*	Persist*	Exit*
2000	161,334	37,114	-	-	27,560	-
2001	167,485	40,330	3,413	3,516	28,347	43,115
2002	180,144	45,245	5,051	4,329	31,061	25,811
2003	196,061	50,901	4,884	4,073	34,740	31,573
2005	271,270	75,604	9,252	5,859	49,837	61,359
2006	301,289	79,288	8,320	8,695	52,625	26,815
2007	335,958	79,072	7,889	12,402	57,705	28,728

Notes: "Quit" refers to firms that quit the export market while "Exit" refers to firms that exit the dataset. Those firms may either close down or shrink their sales below the threshold. "Persist" denotes firms that keep exporting all periods covered by the dataset.

All monetary variables are deflated to 2000 based on the industrial-level PPI data from China Statistical Yearbook (from 2000 to 2007). Firms are aggregated at the 2-digit level, which generates 33 industries. Exports performance is quite uneven across industries. See Appendix A.1 for the analysis of exports across industries. In five industries, i.e., fur, leathers, and feathers, apparels, recreation products and craftwork, the number of exporters exceeds that of non-exporters, as illustrated in Figure 2.1. This finding is inconsistent with the arguments from Clerides et al. (1998); Bernard and Jensen (1999), both of which report that exporters account for only a small proportion of firms within each respective industry for the U.S. and Columbia. Such discrepancy might due to the sample selection effect, i.e., firms covered in this dataset are basically large-and-medium-size firms which are more likely to export. This finding shows that those industries in China are export-oriented.



Notes: See Table A.3 in Appendix for the concordance of 2-digit code and the industry.

Figure 2.1: Numbers of Exporters and Non-exporters by Industry

2.2.2 Preliminary analysis

The Kolmogorov-Smirnov test is applied to examine whether the performance of exporters dominates that of non-exporters systematically. The test is based on the theory of first-order stochastic dominance. The two-way and one-way tests are conducted to examine the equality of the two distributions between exporters and non-exporters in terms of labor productivity, capital, the number of employees, revenue, investment, and the ratio of new product to output[2]. As shown in Table 2.2, the combined K-S two-way test rejects the

Table 2.2: Kolmogorov-Smirnov Test

Smaller Group	Productivity	Capital	Labor	Revenue	Investment	PInnovation
Non-exporter	0.0203***	0.106***	0.249***	0.191***	0.164***	0.116***
Exporter	-0.0603***	-0.000	0.000	0.000	-0.000	0.000
Combined K-S	0.0603***	0.106***	0.249***	0.191***	0.164***	0.116***

*Notes: Significance level: * $p < 0.1$, ** $p < 0.05$, ***$p < 0.01$. Productivity refers to labor productivity, measured by the value added per worker.*

null hypothesis on the equality of distribution of exporters and non-exporters for all variables in question. The one-way test shows that non-exporters is significantly dominated by exporters in terms of capital, labor, revenue, investment, and production innovation. However, one-way test for exporters on labor productivity rejects the hypothesis significantly, suggesting that non-exporters are not uniformly dominated by exporters in terms of labor productivity. Appendix Figure A.2 compares the cumulative distributions of exporters and non-exporters in terms of these variables. Non-exporters are dominated by exporters in terms of all characteristics except for labor productivity whose distribution curves for the two groups show an overlap. This implies that labor might be a key to understand the differences between exporters and non-exporters. Therefore, Figure 2.2 further compares firms that export all the time (Persist) with firms that never export (Never) for both the aggregate and labor-weighted characteristics.

As can be seen from the left side of Figure 2.2, persistent exporters have higher levels of capital, value-added, sales, and size (the number of employees)

[2]Let F and G be cumulative distribution functions of firms' characteristics for two subsamples to be compared (exporters or non-exporters). First-order stochastic dominance of F relative to G is defined as $F(z) - G(z) \leqslant 0$ uniformly for any $z \in \mathbb{R}$, with strict inequality for at least one z. Combined Kolmogorov-Smirnov two-way test: $H_0 : F(z) - G(z) = 0\ for\ all\ z \in \mathbb{R}\ vs.\ H_1 : F(z) - G(z) \neq 0\ for\ some\ z \in \mathbb{R}$. One-way test: $H_0 : F(z) - G(z) \leqslant 0\ for\ all\ z \in \mathbb{R}\ vs. H_1 : F(z) - G(z) > 0\ for\ some\ z \in \mathbb{R}$.

compared to never-exporters. However, when these indicators are divided by the number of employees, the reverse trend appears, except for the average wage. As shown in the right column of Figure 2.2, never-exporters exhibit the catching-up trend in terms of labor productivity and sales per worker. Moreover, they are more capital-intensive across all period.[3]

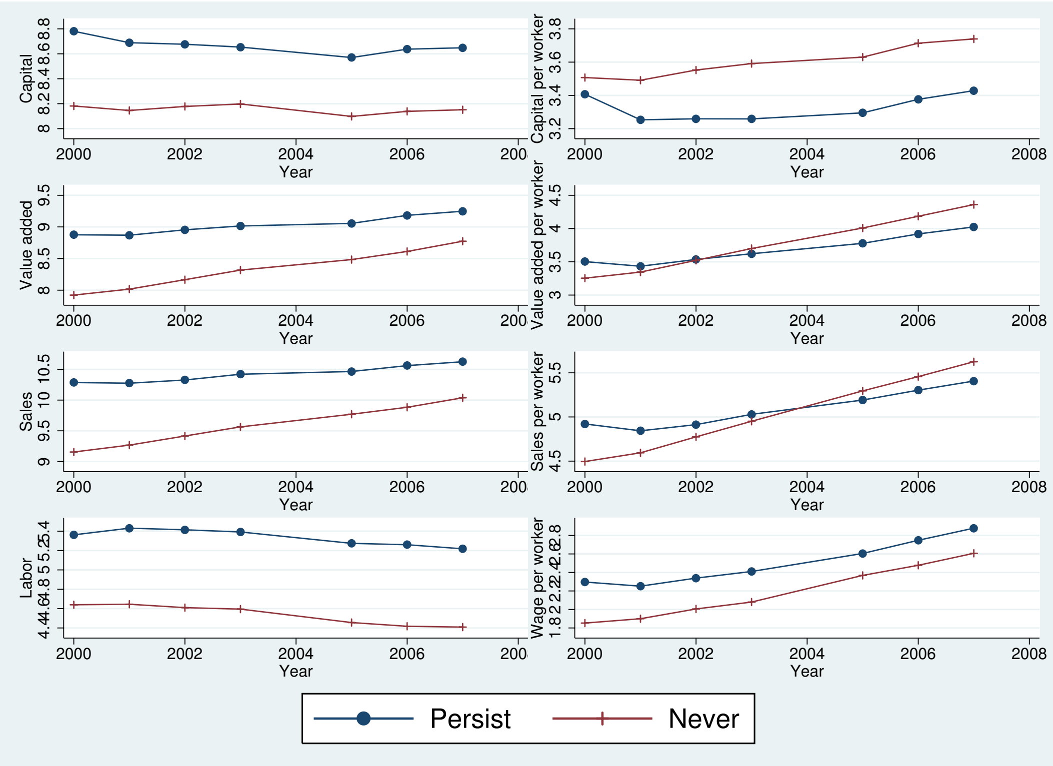


Figure 2.2: Firms Characteristics: Gross and Labor-weighted Indicators

2.2.3 Productivity trajectory

In order to illustrate the dynamic trend of productivity for different groups, Figure 2.3 plots the trajectories of labor productivity for persistent exporters, exporting starters, never-exporters, and all firms within industries from 2000

[3]The similar pattern holds for other characteristics such as investment and output, as well as at the industrial level. These results are available at requests.

through 2007 in apparel, pharmaceuticals, ICT (telecommunications, computer and electronics), and chemical materials and products. The timeline is rescaled for firms that start to export (*starter*). The year when firms enter the export market corresponds to 2004. Firms that exit the export market are dropped from this analysis in order to keep the comparison consistent.

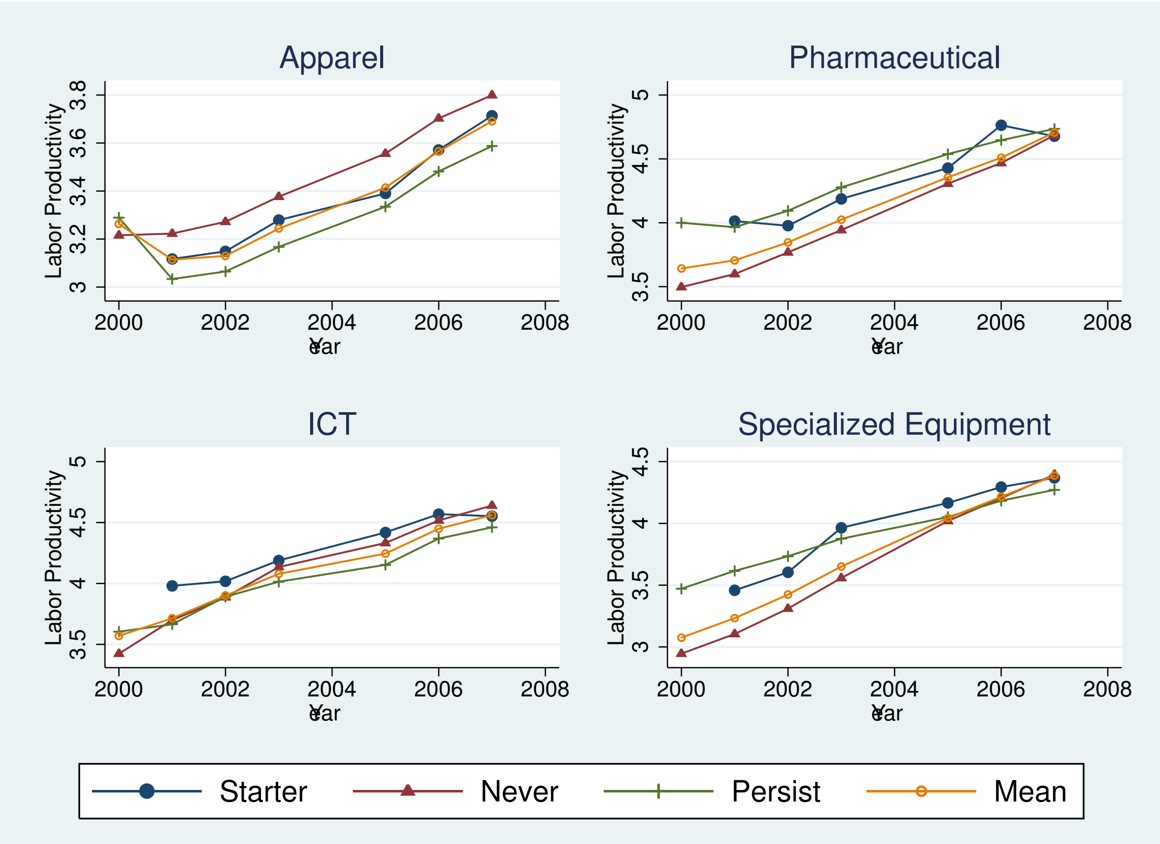


Figure 2.3: Productivity Trajectory by Industries

Changes in the productivity for export starters after 2004 reflect the learning-by-exporting effect, while the performance prior to 2004 indicates the self-selection effect. Although the post-export performance is divergent across four industries, never-exporters exhibit the fastest growth trend compared to starters and persistent exporters, showing a catching-up tendency with various magnitudes across industries. In labor-intensive sectors, for example, apparel, less productive firms export while in more capital-intensive sectors, such as ICT, pharmaceutical and specialized equipment, starters are on average more productive than never-exporters. This evidence implies a different self-selection effect for firms in labor-intensive and capital-intensive sectors to enter the international market. Moreover, it also suggests the relevance of industry's peculiarity to the post-entry performance of exporters. The causal link between exporting and the performance of firms cannot be drawn based on the OLS regression in the sense that it is not clear whether firms are different before they enter the export market or it is the export market participation that leads to this diverging performance. Hence, more elaborate econometric analysis is required to disentangle the self-selection effect (either negative or positive) from the learning-by-exporting effect.

2.3 The Econometric Model and Identification Strategy

This section constructs an econometric model to identify the productivity change in post-export period between exporters and their counterfactual firms – exporters that would not export, formulized as equation (2.1).

$$E[p^1_{t+s} - p^0_{t+s}|XP_{i,t} = 1] = E[p^1_{t+s}|XP_{i,t} = 1] - E[p^0_{t+s}|XP_{i,t} = 1] \qquad (2.1)$$

where p_{t+s} denotes the productivity in the sth post-exporting period;

XP is binary exporting indicator, with 1 for a exporter;

The superscript indicates the exporting activity, with 1 for exporting.

This counterfactual effect $E[p^0_{t+s}|XP_{it} = 1]$ is, however, unobservable. The OLS estimation would be vulnerable to the simultaneity problems and self-selection bias. The former arises due to the bi-directional causality between export decision and productivity, and the latter is related to the argument that exporting starters perform differently from non-exporters. This chapter implements the matching strategy to correct for the selection bias (either positive or negative) and simultaneity problems by constructing the counterfactual effect with observable variables using the group of never-exporters.

More specifically, the propensity score matching (hereafter as "PSM") (Rosenbaum and Rubin, 1983) is applied to identify comparable groups of never-exporters which have similar propensities to export with exporting starters within each industry. The probability that firms will start exporting is specified as a function of the lagged TFP ($TFP_{i,t}$) and the other characteristics, including capital ($CAP_{i,t}$), wages ($WAG_{i,t}$), labors ($LAB_{i,t}$), intermediate input ($INM_{i,t}$), investment ($INV_{i,t}$), the ownership dummy (OWN), and the year dummy (YER), shown as the following equation.

$$Pr(Start_{i,t+1}) = F(TFP_{i,t}, CAP_{i,t}, WAG_{i,t}, LAB_{i,t}, INM_{i,t}, INV_{i,t}, OWN, YER)$$

Following De Loecker (2007) and Greenaway and Kneller (2008), the learning effect is identified through a difference in difference (DiD) estimator, formulized as equation (2.2). By comparing the weighted average difference between the change in productivity of exporters and that of matched non-exporters, this DiD estimator is able to eliminate the unobserved time-invariant heterogeneity of firms. Consequently, the combination of PSM and DiD estimators can improve the quality of non experimental evaluation studies (Blundell and Dias, 2000; Smith and Todd, 2005).

$$\beta^s_{DiD} = \frac{1}{N_s}\sum_i \{(p^1_{t+s,i} - p^1_{t,i}) - \sum_{j\in C(i)} w_{ij}(p^c_{t+s,j} - p^c_{t,j})\} \tag{2.2}$$

where w_{ij} denotes the weight of the propensity score, depending on the matching method. The Kernel matching and the nearest neighbor matching are used in the following analysis;

N_s is the number of firms in each group for each period s;

$C(i)$ denotes the control group.

2.4 Results

First, Total Factor Productivity (hereafter as "TFP") is estimated within each industry using the semi-parametric method proposed by Olley and Pakes (1996), assuming that firms in the same industry follow the same production function. This method is able to correct for the selection bias caused by the exit of firms and the simultaneity problem between capital and productivity by using investment as the instrument in a two-step estimation. Van Beveren (2007) reviews different estimation methodologies and confirms that the semi-parametric estimators, especially Olley and Pakes estimators, are better than the GMM and fixed effects estimators in the presence of imperfect competition and endogeneity of product choice.

2.4.1 Matching algorithm

Matching is conducted at the 2-digit industrial level based on equation (2.3) as preliminary analysis suggests that exporters in various sectors differ in their relative performance to non-exporters. For example, in the labor-intensive sectors, less productive firms tend to export, while the situation is reversed in more capital-intensive sectors. There are no theoretical benchmarks for choosing the variables for matching (Todd, 2008). This specification is assumed because it fulfills the balancing test proposed by Rosenbaum and Rubin (1983) and Becker and Ichino (2002). The test requires the mean of each covariate does not differ between treated and control units. This guarantees that the outcome variable is mean independent of the treatment indicator conditional on the propensity score ($D \perp X | P(X)$). The standard t-test for the equality of means of the covariates is also implemented to assess whether significant differences remain conditional on the common support group, signifying the reliability of propensity score matching.

Matching is processed across various years and the timeline is accordingly rescaled based on the event (the start of exporting). In such way, if a firm decides to start export at time 0, the same also holds for the matched control firms (non-exporters). In other words, the time at which a non-exporter is matched to a certain export starter is set to zero, no matter what the calendar year is. The set $s = \{0, 1, 2, ...\}$ denotes the post-export time periods.

2.4.2 DiD matching estimation

The PSM-DiD estimators on the average post-export effects of productivity level are calculated through the Kernel weight at every period within each industry. The overall average treatment effect for the whole sample is estimated using 10-nearest neighbors for firms on common support at each post-entry period. Bootstrapped standard errors are obtained using the industrial strata. As an alternative, the aggregate effect can be calculated as the mean of the estimators from industrial levels, weighted by the number of treated firms in each industry. This method does not generate interference information. Table 2.3 shows the DiD matching estimator for TFP, labor productivity, as well as product innovation. The mean value of DiD matching estimators are determined values, shown in the row "Mean" as a reference.

The DiD estimator on TFP only shows a significantly positive sign when firms enter the exporting market (See Appendix Table A.2 for estimators on each separate industry. Exporters in paper-making, general equipment and coal mining experience the increases in productivity compared to matched non-exporters when foreign sales are initiated.). The mean values are quite similar to the estimators from DiD 10-nearest neighbors matching. In general, exporting does not lead to a higher level of labor productivity for exporters in China. DiD matching estimators on labor productivity for the first and the third post-export periods even have the negative signs, although none of these coefficients are statistically significant. The similar result holds for separate industries.[4]

[4]The result is not covered in the chapter, available at requests.

Because labor productivity can partially represent firms efficiency, and the estimated TFP may include more unexplainable factors than efficiency, this chapter adopts the product innovation, measured by the ratio of new product value to output, as a more straightforward indicator for the outcome of learning. As shown in third tier of Table 2.3, the estimator on product innovation is significantly positive when firms start exporting, with 2.7 percent of improvement, while results for other periods do not show significantly positive signs. The first post-export period even produces a significantly negative sign (-0.005).

Table 2.3: DiD Matching Estimator

Indicator	β_{DiD0}	β_{DiD1}	β_{DiD2}	β_{DiD3}	β_{DiD4}	β_{DiD5}
TFP	0.051**	0.007	0.022	0.045	0.044	0.071
	(0.028)	(0.023)	(0.016)	(0.028)	(0.031)	(0.056)
Mean	0.048	0.007	0.012	0.042	0.037	0.048
Controls	978,756	988,546	623,543	349,866	204,612	112,221
Treated	36,635	26,845	16,855	8,213	4,669	1,681
Labor Productivity	0.022	-0.009	0.027	-0.014	0.002	-0.012
	(0.017)	(0.019)	(0.020)	(0.025)	(0.042)	(0.081)
Mean	0.034	0.026	0.012	0.014	0.015	0.010
Controls	987,974	997,901	629,795	353,777	206,578	113,267
Treated	36,917	26,990	16,943	8,270	4,702	1,691
Product Innovation	0.028***	-0.005*	-0.005	0.010	0.005	0.023
	(0.003)	(0.003)	(0.928)	(0.327)	(0.007)	(0.010)
Mean	0.027	-0.004	-0.003	0.011	0.009	0.024
Controls	1,021,837	1,032,346	653,753	368,580	215,664	118,578
Treated	38,296	27787	17,468	8,506	4,835	1,747

*Notes: Bootstrapped standard errors in parentheses. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. "Mean" denotes the mean of DiD matching estimators by industries. "β_{DiDs}" denotes the s^{th} post-exporting period.*

The result indicates that firms engage in more product innovation in order to penetrate the international market, while the trend does not continue in later post-export periods. This is in line with the finding by Costantini and Melitz (2007) that the expectation of entering the export market induces firms to pursuit the production innovation. The result holds for estimations at each separate industry. As shown in the Appendix Table A.3, exporters in most sectors display a strong tendency to produce more new products when entering the international market. Those sectors include mining sectors (coal mining, ferrous metal ore mining, nonferrous metals mining and nonmetal minerals mining), food sectors (agricultural food products, food, beverage and tobacco), leather, chemicals, pharmaceuticals, nonmetal minerals manufacturing, metal manufacturing, general equipments, specialized equipments, vehicles, electrical, ICT, craftwork, electricity and steam, and gas. However, in the following periods, the outcome estimators are either not significant or significantly negative in most industries except for tobacco, beverage, and textiles, which again confirms that after firms penetrate the international market, they do not show the evidence of improvement. Sectors are sorted in the descending order with respect to the median level of capital-labor ratio.

2.4.3 Robustness checks

In order to check the robustness of PSM-DiD estimation, we extract a balanced panel sample from the original dataset and estimate it using a separate PSM and DiD regressions. The balanced sample covers 9,850 starters for the year 2000 through 2007.

The matching is among export entrants and never-exporters implemented within each industry at each year. The generated subsample consists of matched non-exporters and exporters on common support in a certain time ($s = 0$). The information on full time periods for these matched firms is then merged to construct a panel structured dataset for OLS DiD estimation, as shown in equation (2.3).

$$g_{i,t} = \alpha + \sum_{s=0}^{S} \beta_s \cdot 1\{t_{i=s}\} + \gamma EXP_i + \rho DiD_i + \beta_{\mathbf{x}} \mathbf{X_{i,t-1}} + \epsilon_{i,t} \tag{2.3}$$

where $g_{i,t+1}$ is the outcome variable, which can be either productivity or the ratio of new product value to output;

t_i is a full set of time information;

DiD is the interaction term of t_i and EXP, defined as 1 for the exporter group at the time period when firms export. This variable captures the average post-export effect on the improvement in productivity among exporters and never-exporters across the observed periods;

$\mathbf{X_{i,t}}$ is a series variables of firms' characteristics at t;

$\epsilon_{i,t}$ is the error term.

The variable t_s (s=0, 1, 2, 3, 4, 5) captures the time trend effect. Serial correlation may occur in such multi-period OLS DiD regression. This problem may lead to the underestimation of the standard deviation on estimators and to generate the inconsistent standard errors. Bertrand et al. (2004) point out that the block bootstrap performs well in estimating standard errors for large samples in the presence of the cross-sectional heteroscedasticity and arbitrary serial correlation problems.

Table 2.4 reports the DiD regression results on TFP and the ratio of new product value to output respectively. The block bootstrapped standard errors are clustered within firms. The DiD coefficients in TFP regression are not significant for any periods expect for the fifth post-export period with a negative sign. This result is consistent with the PSM-DiD estimation. None of DiD coefficients in the regression on product innovation are significant. In particular, exporters do not show the significantly positive increases in production innovation compared to the matched never-exporters when they start to export (s=0). This might due to the fact that matching is conducted at time zero using the present variables (not the lagged variables as in PSM-DiD estimation), which drives out the idiosyncratic shocks that make firms decide to export.

Table 2.4: OLS DiD Regression

	TFP		Product Innovation	
	β	SE	β	SE
DiD0	0.010	(0.02)	-0.001	(0.00)
DiD1	0.019	(0.03)	-0.003	(0.01)
DiD2	-0.028	(0.03)	0.001	(0.01)
DiD3	-0.004	(0.03)	0.002	(0.01)
DiD4	-0.011	(0.03)	0.006	(0.01)
DiD5	-0.092*	(0.04)	0.010	(0.01)
t1	0.016	(0.01)	-0.002	(0.00)
t2	0.056***	(0.02)	0.006	(0.00)
t3	0.041***	(0.01)	0.001	(0.00)
t4	0.031**	(0.01)	-0.002	(0.00)
t5	0.077***	(0.01)	-0.003	(0.00)
Export	0.048***	(0.01)	0.058***	(0.00)
lagTFP	0.685***	(0.00)	0.006***	(0.00)
lagLabor	-0.021***	(0.01)	-0.014***	(0.00)
lagCapital	0.011***	(0.00)	0.008***	(0.00)
lagWage	0.047***	(0.01)	0.021***	(0.00)
Constant	0.576***	(0.04)	-0.197***	(0.01)
Ownership	Yes		Yes	
Industry	Yes		Yes	
Obs.	61,265		62,080	
R2	0.664		0.105	

Notes: Block bootstrapped standard errors in parentheses. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.5 Interpreting the Lack of Evidence of Learning-by-exporting

2.5.1 Labor dominates the expansion of exporters

In order to decompose the source of growth for exporters, the changes in labor, capital, and value-added over time are estimated and compared between exporting starters and their matched domestic-oriented firms for each year (in the similar manner to PSM-DiD). Figure 2.4 portrays the differences of changes in those variables between exporters who initiate their foreign sales in 2002 and matched never-exporters over time. In more labor-intensive sectors, the trajectory of difference in changes of labor shows the steepest trend, as compared to that of valued-added and capital, shown on the left of Figure 2.4. This implies that exporters expand by virtue of employing more workers in labor-intensive sectors. Although value-added changes faster than other factors in capital-intensive sectors (on the right of Figure 2.4), the differences in labor changes for exporters are higher than those of capital. Therefore, it can be argued that labor dominates the expansion of Chinese exporters, and that lower labor cost may be a fundamental factor in supporting the expansion of Chinese exporters.

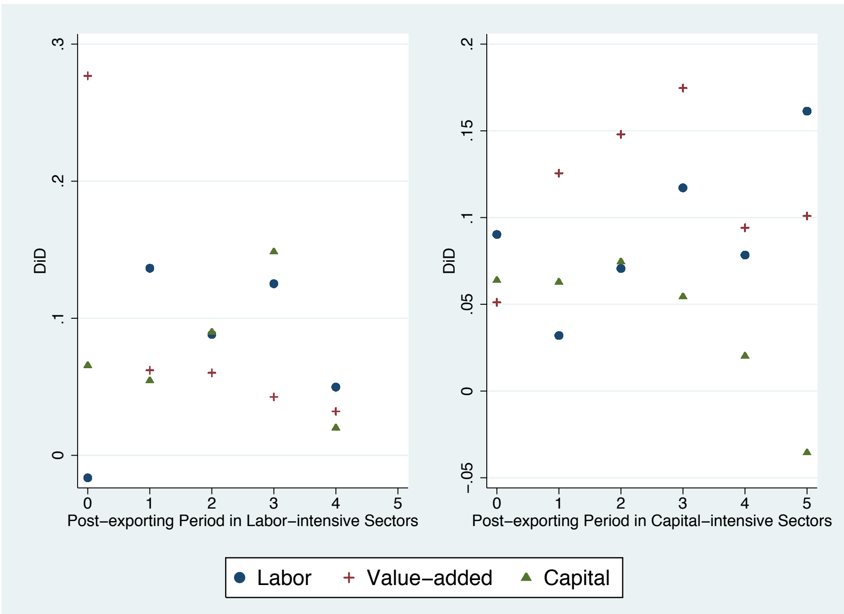


Figure 2.4: DiD Trajectory on Firm Characteristics

Notes: The division of labor- or capital-intensive sectors is based on the median level of capital-labor ratio for each industry, with 3.7 as the devision point.

The prominent usage of labor by exporters can be seen from Figure 2.5 where the average number of employees, TFP, and labor productivity are compared along the increasing of the export intensity. The export intensity, measured by the ratio of export value to sales, is divided into 100 bins from 0 to 1 in intervals of 0.01. Firms are grouped according to their export intensities. The performance of non-exporters corresponds to the value at zero point of export intensity bin. It is obvious that exporters hire more employees than non-exporters across all intensity bins, but are not necessarily more productive than nonexporters. The productivity of exporters shows a strikingly decreasing trend relative to the increasing of export intensity. Groups with lower export intensity perform the best on average.

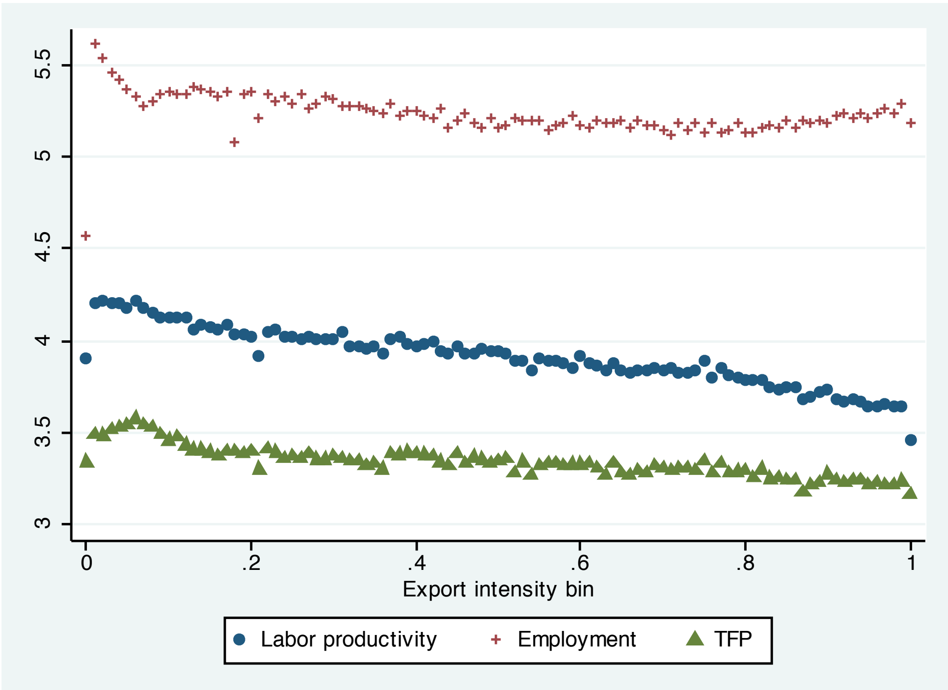


Figure 2.5: Productivity and Employment across Export Intensities

Notes: Points at zero correspond to the performance of non-exporters.

The high demand for labor by exporters suggests that the performance of exporters may differ in sectors with varying factor requirements. Lu (2010) points out that the less productive firms (in terms of labor productivity) in China enter the export market in labor-intensive sectors, while the trend is reversed in capital-intensive sectors. Domestic-oriented firms may face more competitive environments than exporters in labor-intensive sectors in China because exporters in those sectors take advantage of relatively cheap labor. Extending Lu (2010)'s argument to TFP, Figure 2.6 presents that differences in productivity of exporters and non-exporters increase along labor-intensive to capital-intensive industries, with values ranging from -0.23 (leather) to 1.58 (petroleum) for TFP and from -0.39 (leather) to 1.72 (tabacco) for labor productivity. The industry's feature with respect to factor requirements is proxied with the median value of capital-labor (K/L) ratio within each industry. In labor-intensive sectors, such as apparels, leather and recreational products, non-exporters are more productive than exporters.

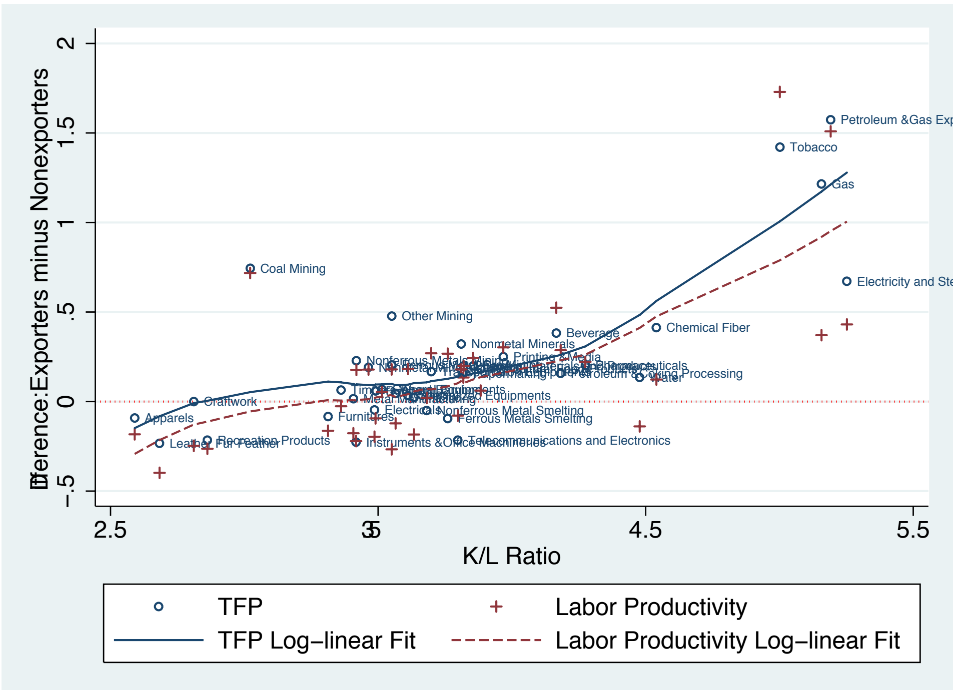


Figure 2.6: Differences on Productivity between Exporters and Non-exporters by Industry

As a supplementary evidence on the differences of labor expanding across labor- and capital-intensive sectors, Figure 2.7 compares changes in industrial structure in terms of both output and size (the number of employees) for exporters and the whole industry between 2000 and 2007. The structural

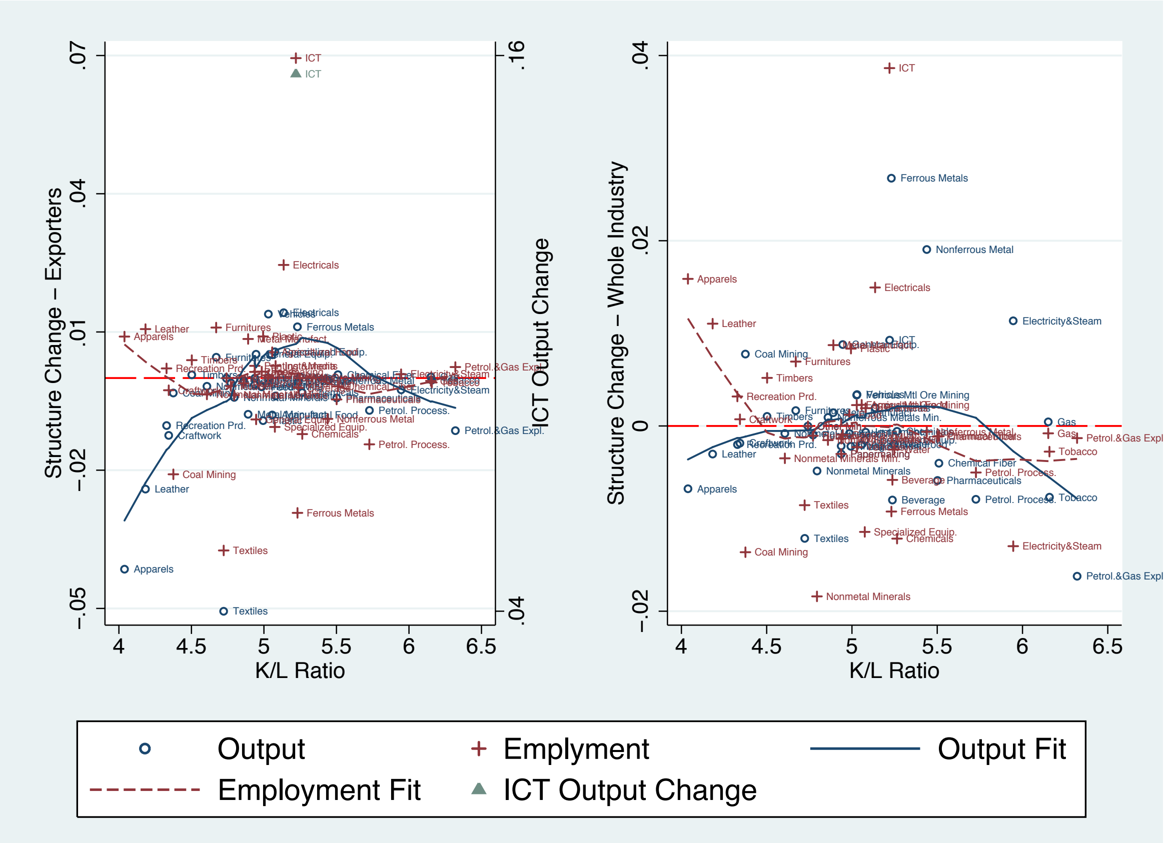


Figure 2.7: Structural Change: Industry and Exporters

change is measured by the percentage change in the fraction of industrial output (or number of employees) relative to all industries from 2000 through 2007, as shown in equation (2.4).

$$\triangle sc_j = \frac{\sum_{i=1}^{n} x_{i,j}^{2007}}{\sum_{j=1}^{33}\sum_{i=1}^{n} x_{i,j}^{2007}} - \frac{\sum_{i=1}^{n} x_{i,j}^{2000}}{\sum_{j=1}^{33}\sum_{i=1}^{n} x_{i,j}^{2000}} \tag{2.4}$$

where $x_{i,j}^{t}$ denotes the performance (either the number of employees or the output) of firm i in industry j at time t;

$\triangle sc_j$ is the structural change for industry j. They are calculated for all firms and exporters respectively within each industry.

As a benchmark, the percentage changes for exporters and all firms are plotted along a sector's K/L ratio respectively. In general, exporters in labor-intensive sectors, such as apparel, leather, recreation, timbers and furnitures, increase the number of employees relatively (left in Figure 2.7), while tend to shrink their output relatively (right in Figure 2.7). There is a big jump in ICT for changes in both labor and output, followed by electrical industry. Outputs of exporters move towards to sectors featuring with the intermediate level of capital-intensity. The situation of the whole industry follows the similar pattern with that of exporters.

2.5.2 R&D investment is needed for learning

Related to the prominent usage of labors, a deeper reason for the failure of learning is that firms do not put enough efforts to improve productivity. The Neo-Schumpeterian theory emphasizes that firms in developing economies are not passive recipients of advanced technology, and that successful learning requires the deliberate efforts by firms to invest in technology in order to improve the absorptive capacity (Kim, 1997; Kim and Nelson, 2000).

The learning efforts are measured by R&D expenditures. The information about R&D expenditures for Chinese firms is only available for 2005, 2006 and 2007. During this period, 15.2 percent (35,512 out of 233,964) of exporters invest in R&D, with 8.19 percent (55,258 out of 674,553) of non-exporters. R&D intensity is highly skewed towards the lowest level: over half of R&D investors spend less than 0.5 percent of sales on R&D investment. The similar patterns hold for both exporters and non-exporters. See Appendix Figure A.3(a) for the fraction of R&D investors across sectors and Figure A.3(b) for the histogram of R&D investment among exporters and non-exporters.

The OLS regression is used to estimate preliminarily the effect of R&D investment and export on firm productivity, formulized in equation (2.5) and (2.6). The estimation is conducted over exporters, non-exporters, and the whole samples respectively.

$$y_{i,t} = \alpha + \beta RND_{i,t} + \gamma_1 K/L_{i,t} + \gamma_2 (K/L_{i,t})^2 + \sum \delta_j Year_j + \sum_k \lambda_k Ind_k \quad (2.5)$$

where y_{it} denotes either TFP or labor productivity;

The coefficient of binary variable $RND_{i,t}$ can be interpreted as the difference between R&D investors and non-R&D-investors;

Control variables include the capital-labor ratio $K/L_{i,t}$, the year dummy $Year_j$, and the industry dummy Ind_k.

γ_2 is set to zero when the dependent variable is labor productivity. The U-Shaped relationship between TFP and capital-labor ratio is specified based on the analysis in section 2.5.1.

$$\begin{aligned} y_{i,t} &= \alpha + \beta RND_{i,t} + \eta EXP_{i,t} + \rho RNE_{i,t} + \gamma_1 K/L_{i,t} + \gamma_2 (K/L_{i,t})^2 \\ &\quad + \sum \delta_j Year_j + \sum_k \lambda_k Ind_k \qquad (2.6) \end{aligned}$$

where $EXP_{i,t}$ is the binary variable of export, with 1 for exporting;

$RNE_{i,t}$ is the product of $RND_{i,t}$ and $EXP_{i,t}$, with 1 for exporters which invest in R&D;

As before, γ_2 is set to zero when the dependent variable is labor productivity.

The coefficient of $RNE_{i,t}$ can be interpreted as the interaction effect of engaging in both R&D and exporting on improving the productivity of firms. As shown in Table 2.5, the presence of R&D investment shows a significantly positive effect on firm productivity. This result holds for all regressions, with coefficients of 0.250 among exporters and 0.222 among non-exporters. The comparison of these two coefficients suggests that R&D investment may impact more on the productivity of exporters than that of non-exporters. Moreover, the interaction of export and doing R&D has a positive effect on

Table 2.5: Interaction of R&D and Exporting on Productivity

	Exporters				Non-exporters				All Firms	
	TFP		LP		TFP		LP		TFP	LP
RND	0.226***	0.250***	0.284***	0.138***	0.192***	0.222***	0.209***	0.127***	0.227***	0.129***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
K/L		-0.286***		0.314***		-0.353***		0.279***	-0.333***	0.288***
		(0.005)		(0.002)		(0.003)		(0.001)	(0.003)	(0.001)
$(K/L)^2$		0.035***				0.036***			0.035***	
		(0.001)				(0.000)			(0.000)	
EXP									-0.036***	-0.117***
									(0.003)	(0.003)
RNE									0.044***	0.027***
									(0.007)	(0.007)
constant	3.647***	4.158***	4.055***	3.118***	2.973***	3.647***	3.402***	2.596***	3.647***	2.623***
	(0.026)	(0.027)	(0.031)	(0.030)	(0.008)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	230,469	230,469	230,771	230,469	656,209	656,209	658,539	656,209	886,678	886,678
R^2	0.323	0.339	0.122	0.264	0.247	0.271	0.063	0.164	0.284	0.189

Notes: Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *Robust standard errors in parentheses.*

firm productivity in the regression for all firms. However, the exporting status is significantly negative correlated with firm productivity. This evidence tentatively indicates a complementarity of R&D investment and exporting on firm productivity. In addition, a U-shaped relationship between TFP and K/L ratio is confirmed since the coefficients of $(K/L)^2$ are significantly positive for all TFP regressions.

2.6 Conclusions and Discussion

This chapter investigates the learning-by-exporting hypothesis by testing whether exporting generates higher levels of productivity as well as more product innovations for Chinese firms. It adopts the combination of propensity score matching and difference-in-difference estimation to disentangle the selection effect, which can be either positive or negative, from the learning-by-exporting effect. The evidence does not show that Chinese firms generate significant increases in productivity through exporting. This result holds for both the whole sample and the separate industries. However, in order to penetrate the international market, firms conduct more product innovation when foreign sales are initiated. This effort, however, does not continue in the following post-export periods. A separate PSM and DiD regression on the balanced panal data basically confirms these results.

Further, this chapter explores why exporters in China fail to show the supportive evidence of productivity improvement. On the one hand, labor dominates the expansion of exporters. Compared to the matched non-exporters, exporters experience the faster changes in labor than in value-added and capital. This result implies that exporting may generate more jobs but not necessarily improve firms efficiency. On the other hand, exporters need to invest in R&D in order to absorb the advanced technology available in the international market. The combination of exporting and conducting R&D is positively correlated with firms productivity. The presence of R&D investment shows a significantly positive effect on the productivity for both exporters and nonexporter, although the positive effect for exporters is larger than for non-exporters. Moreover, the prominent usage of labor by exporters results in a lower level of productivity than that of non-exporters in labor-intensive sectors. Consequently, these results suggest that lower labor costs may still serve as a fundamental factor in supporting the exporting of Chinese firms.

As with exporting, the decision of firms to invest in R&D might be self-selective. Firms' other characteristics, observable or unobservable, may lead to both decisions. More sophisticated models and empirical analyses on complementaries between exporting and investing in R&D are to carried out in future studies.

Chapter 3

Complementarities Between R&D Investment and Exporting: Theory and Evidence

3.1 Introduction

This chapter explores a potential complementarity between the decision for firms to export and invest in R&D, both theoretically and empirically. Due to the inconclusive support for the causal link between exporting and the productivity boost of firms, more studies have sought to analyze how exporting interact with other productivity-enhancing activity, such as investment in technology (Bustos, 2011; Aw et al., 2008). With respect to the situation of firms in China, Wang and Xu (2011) argue that exporting does not generate higher productivity for Chinese firms while the interaction of R&D investment and exporting is positively correlated with the productivity of firms. The positive effect of R&D investment on productivity is larger for exporters than non-exporters. Consequently, firms need to exert the deliberate effort, for example, investing in R&D, to absorb the advance technology available in the international market in order to attain the productivity gains through exporting. However, the decisions of firms to either conduct R&D or export might be determined by other factors and these two activities might interact with each other. For this reason, this selection effect with respect to firms decision should be considered when the impact of the interaction of two decisions on the performance of firms is analyzed.

This chapter investigates a potential complementarity between R&D investment and exporting in two aspects: (1) whether the decision to export induces Chinese firms to invest in R&D and vice versa; (2) whether exporting and R&D investment have a complementary impact on improving the performance of firms in China. In fact, both questions are presumed to lead to the same conclusions because firms make decisions based on their expectations on the potential gains in profits.

From the empirical point of view, China is a particularly interesting case to analyze due to its fast-growing economy as well as its dramatic emergence in the international market. As the world's largest exporter in 2009, China has raised the ratio of export to GDP from 18 to 36.5 percent since 2000. In contrast, the share of R&D expenditures to GDP has only increased from 0.9 to 1.5 percent in China during the same period. Furthermore, Chinese exporters are not generally more productive than their domestic-oriented counterparts, inconsistent with findings of other empirical studies and theories (Lu, 2010). Relatively cheap labor has been shown important for the expansion of exporting firms in China (Wang and Xu, 2011). Consequently, the comparative advantages of China may still lie in the labor-intensive sectors. This chapter aims at understanding how the export decision of Chinese firms interacts with their decision to invest in R&D, and how the comparative advantages relate to, and are influenced by the two decisions.

The main result of the chapter can be summarized as follows. First, there is a systematic difference between the labor-intensive and capital intensive sectors in terms of productivity and the export decision of firms.

Less productive firms tend to export in the labor-intensive sectors while the productivity does not significantly impact on the export decision of firms in the capital-intensive sectors. Second, more productive firms select themselves into conducting R&D in China, though the exporting status lowers the threshold of productivity for firms to start R&D. Third, exporting is observed to have a positive effect on the decision of firms to invest in R&D and vice versa, thus demonstrating a feedback within the decision-making of firms. Fourth, the interaction of R&D investment and exporting is identified to have a complementary effect on improving the productivity of firms using a multinomial treatment effect model in which the self-selection bias from different decisions is corrected through a mixed multinomial logit regression. In order to guide the empirical analysis in this chapter, I develop a theoretical model by introducing both the R&D decision of firms and factor endowments into the model of Melitz (2003). The extended model predicts a complementarity between R&D investment and exporting on the profits of firms.

The rest of this chapter is organized as follows. In the next section, I review the relevant literature on the firm performance related to export and invest in R&D. Section three describes the dataset and some preliminary information on the performance of Chinese firms with their decision to export and its interaction with R&D investment. Section four proposes a theoretical model to explain the decision of firms to export and invest in R&D as well as any complementarity between these activities. Section five expands the econometric models to explore its relevance to the experiences of Chinese manufacturing firms. The last section summarizes the main research findings and offers some policy implications.

3.2 Literature Review

A stylized fact that more productive firms enter the international market has been explained substantially by the model of Melitz (2003), in which a fixed entry cost distinguishes more productive firms to export. Market selection then increases the aggregate level of productivity in response to trade by forcing the least productivity firms to exit and reallocating resources towards more productive exporters within the industry (Melitz, 2003; Ghironi and Melitz, 2005). This expected improvement of productivity, however, is not robustly support in the literature, implying that learning-by-exporting does not freely happen and may require a conscious effort by firms.

Instead of treating learning as a by-product of the exporting, recent studies have paid more attention to the interaction between exporting and other productivity-enhancing decision, such as investment in R&D (Costantini and Melitz, 2007; Aw et al., 2008; Mayneris, 2010). The purpose of investing in R&D is not only to introduce innovation, but also to adapt and absorb technology from outside sources, especially for firms in developing economies (Cohen and Levinthal, 1989). R&D investment results in the improvement of productivity by either upgrading the technology (Bustos, 2011), or reducing cost and developing new product mix (Atkeson and Burstein, 2010). Treating investment in technology as an additional fixed cost needed to raise the productivity of firms, Lileeva and Trefler (2010) and Bustos (2011) demonstrate that the exporting experience induces firms to invest in technology because the presence of a larger market through exporting can spread out the fixed costs required by R&D investment, and thus make the investment more profitable. Consequently, the expectation of penetrating the international market induces firms to pursue product innovation (Costantini and Melitz, 2007). The subsequent increases in productivity achieved through R&D investment conversely lead firms to the export market. Hence, a bidirectional feedback relationship exists between the exporting and R&D investment activities of firms.

The decisions of firms to conduct R&D and export are regarded as market selection mechanism. Due to the necessary upfront cost of R&D investment, only the more productive firms select themselves to pursue such opportunities. The underlying pattern is that the most productive firms export and use advanced technology, the intermediate group exports but still uses less-advanced technology, while the least productive firms use the less-advanced technology and only serve the domestic market. The subsequent gains from the exporting experience are heterogenous across firms. The potential learning through exporting only happens to firms that engage in R&D activities or technology upgrading (Lileeva and Trefler, 2010).

Many empirical studies demonstrate a positive interaction between the decision to export and that of pursuing R&D investment. For instance, when facing higher reductions in Brazil's import tariffs, Argentinian firms have been observed to increase their investment in technology faster, meanwhile exporting firms upgrade their technology faster than other firms in the same industry (Bustos, 2011). Furthermore, in the context of the UK, those firms that have utilized R&D activities to develop their absorptive capacity not only experience significantly reduced entry barriers into export markets, but are also able to further improve export performance, in detriment to those firms which have not invested (Harris and Li, 2009). The intensity of R&D investment is also positively correlated with the exporting status for Indian manufacturing firms (Parameswaran, 2009). Aw et al. (2008) document an increasing return for R&D investment through the larger market share for exporters in Taiwanese electronics industry. Both R&D investing and exporting have a direct, positive effect on the potential productivity of firms, but when estimated as discrete decisions, the effect of R&D is larger.

Wang and Xu (2011) uncover a systematic difference in firm productivity between labor-intensive and capital-intensive sectors in China created by their decision to export and invest in R&D. In the labor-intensive sectors, exporters that do not invest in R&D present the lowest level of productivity, while non-exporters undertaking R&D activities attain the highest productivity. Meanwhile, exporters that invest in R&D are the most productive in capital-intensive sectors.

This systematic difference cannot be explained by most established theories, which basically follow Melitz's (2003) seminal work and assume labor as the only production factor. The single-factor assumption, applied to the context of symmetric countries, conceals the role of sector's peculiarity on the export decision of firms. Therefore, these models are not able to explain the variation in performance of exporting firms across sectors. Bernard et al. (2007b) build a two-country-two-sector model by introducing H-O theory into the Melitz's (2003) model, thereby treating skilled workers and unskilled workers as two separate production factors. Using this model, they predict that the productivity threshold necessary to enter the export market decreases in comparative advantage sectors and is possibly lower than the level of productivity required for firms to survive. However, they then neglect this possibility and constrain their analysis to the scenario where the more productive firms export. Acknowledging the importance of a sector's factor requirements in understanding the export patterns in China, Lu (2010) introduce factor endowments to heterogeneous firm model to explain the structure of export intensity across Chinese firms and argues that the more productive firms tend to serve the tougher market, which would be the more labor-intensive sectors in China. However, none of the existing theories are able to explain the systematically different patterns regarding on the productivity of firms with their decision to export and invest in R&D across labor-intensive and capital-intensive sectors in China. Additionally, the existing theories have not proven the complementary impact of R&D investment and exporting on firm performance.

This chapter incorporates R&D investment and factor endowments into Melitz (2003) model in order to explain empirical findings from Chinese firms, especially demonstrates the existence of a complementarity between exporting and R&D investment on the subsequent performance of firms.

3.3 Empirical Evidence from Chinese Manufacturing Firms

3.3.1 Data

The data comes from the Annual Survey of Chinese Enterprises (ASCE) for the period of 2005 to 2007. Collected and maintained by the National Bureau of Statistics, China, the ASCE compiles all state-owned firms and non-state-owned firms with at least five-million RMB annual sales from manufacturing sectors, identified at the 4-digit industrial level.[1] These firms are defined as "large-and-medium-size enterprises" in China, accounting for around 25 percent of all registered firms. They contribute around 70 percent of total export value, and over 50 percent of total R&D expenditures in China for each year. The survey provides detailed information about the financial performance of firms through variables such as identification, assets, exports, liabilities, capital structure, employment, R&D expenditures, sales, and investment, each of which is available for approximately 271,000 to 336,000 firms each year. compose an unbalanced-panel structure.

Table 3.1 describes the sample size for each of the different categories. R&D investors account for around 10 percent of total firms sampled, with an increasing trend along time. The number of firms starting R&D investment (R&D Starter) surpasses that of firms newly entering the export market (EXP Entrant) for every year of the sample. The descriptive statistics for each variable is shown in Table B.2 of Appendix.

The correlation structure variables is shown in Table A.1. See Appendix Table B.1 for the explanations and measurements of each variable. Export and R&D are significantly correlated (0.102). This is neither sufficient nor

[1]The dataset also covers firms in three service sectors, but those firms are included in the survey simply because they were classified as manufacturing firms before 2003. I therefore restrict the analysis to manufacturing sectors in order to keep the classification consistent.

Table 3.1: The Sample Size

Year	Sample	Exporter	R&D	EXP*R&D	EXP Entrant	R&D Starter
2005	271,270	75,604	25,852	10,253	-	-
2006	301,289	79,288	29,828	11,856	8,111	10,021
2007	335,958	79,072	35,090	13,403	7,747	11,555
balanced	220,643	191,125	75,090	31,147	13,228	18,964

Notes: The last row of the table reports the number of firms in each respective category for a balanced panel. "EXP Entrant" denotes firms which began to export in that year. "R&D Starter" denotes firms initiating R&D investment for the first time in the dataset.

necessary, however, to assert a complementarity between these variables. The labor productivity (hereafter "LP") of firms, measured by value-added per worker, is negatively correlated with the exporting status, but positively correlated with R&D status. Total Factor Productivity (hereafter "TFP"), estimated using the method by Olley and Pakes (1996), is positively correlated with the export status, although less significant economically (0.005). I use both LP and TFP as the reference in the following analysis because, although LP is more straightforward, it is still an incomplete measure of firm efficiency. Furthermore, while TFP is conceptually more accurate, being a residual of production function, the estimated TFP may capture other unexplainable factors more than productivity *per se*. Nevertheless, LP and TFP produce similar results for most cases in the following analysis.

3.3.2 Firm productivity and the decision to export and invest in R&D

First, the mean value of LP and TFP for export entrants (firms that start to export), R&D starters (firms that begin to conduct R&D) and all firms within a given sector (i.e. the industrial mean) are compared at the sectoral level in Figure 3.1. Firms are aggregated at the 2-digit industrial level, which

Table 3.2: Cross-correlation Table

Variable	Export	R&D	LP	TFP	VAD	Labor	Capital	Avwage	K/L	Invest
Export	1.000									
R&D	0.102	1.000								
LP	-0.080	0.087	1.000							
TFP	0.005	0.044	0.664	1.000						
VAD	0.162	0.232	0.631	0.493	1.000					
Labor	0.284	0.206	-0.204	-0.041	0.630	1.000				
Capital	0.121	0.210	0.172	-0.052	0.610	0.595	1.000			
Avwage	0.146	0.164	0.328	0.201	0.280	0.025	0.185	1.000		
K/L	-0.078	0.096	0.377	-0.032	0.252	-0.064	0.764	0.210	1.000	
Investment	0.158	0.270	0.229	0.122	0.499	0.436	0.516	0.250	0.309	1.000

Notes: All results are significant at p<0.001 level. "VAD" denotes value added. "LP" denotes labor productivity, measured by value added per worker. "avwage" is wage per worker. TFP is estimated using method by Olley and Pakes (1996). K/L is capital-labor ratio. Except for the Export and R&D dummy, all variables are in logarithmic form.

generates 33 sectors. The characteristics of a sector is captured by the median level of capital-labor ratio (K/L). Although LP and TFP follow a different trend in relation to the K/L ratio, the relative relationship between the performance of export entrants, R&D starters and all firms within each sector remains similar between LP and TFP. In general, a systematically different pattern occurs with respect to the export decision when comparing the labor- and capital-intensive sectors. Export entrants are not distinctly more productive than the sectoral average in labor-intensive sectors and are actually less productive in leather, apparel, craftwork, the mining of nonmetals and furniture. Conversely, the more productive firms in highly capital-intensive sectors are able to participate the exporting market. There is an obvious self-selection tendency for firms to conduct R&D due to the fact that R&D starters are more productive than the sectoral average. Moreover, they also show better performance than export entrants in most sectors, but in highly capital-intensive sectors, the performance of export entrants surpasses that of R&D starters, such as those in the pharmaceuticals and tobacco industries. R&D starters attain the highest level of productivity in labor-intensive sectors, while export entrants perform the best in highly capital-intensive sectors.

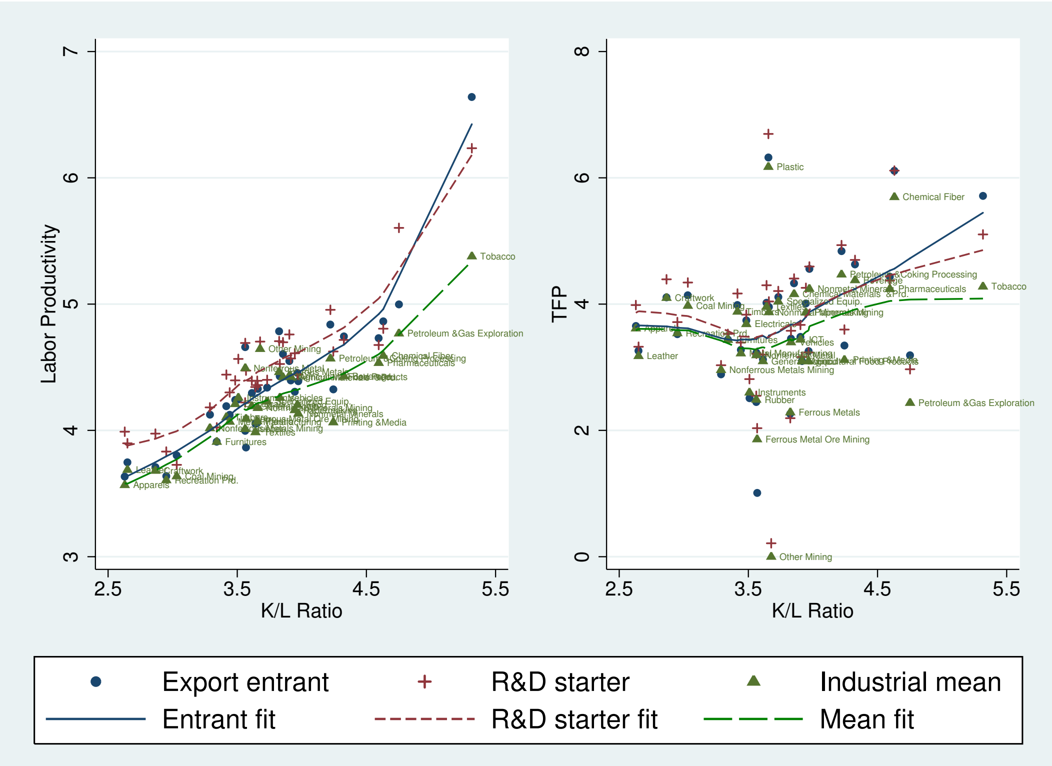


Figure 3.1: Productivity and the Decisions of Firms across Sectors

Notes: TFP is estimated with the method of Olley and Pakes (1996). Log-linear smooth fit. K/L ratio is the median level of capital-labor ratio within each industry.

Furthermore, I investigate the interaction between the decisions to export and invest in R&D by analyzing the productivity of R&D starters conditional on their export status, illustrated in Figure 3.2. Again, note that a systematic difference exists between labor-intensive and capital-intensive sectors. Among both exporters and non-exporters, more productive firms tend to self-select into investing in R&D as R&D starters typically experience higher levels of productivity than the average performance of groups across all sectors. Additionally, non-exporting R&D starters are more productive than exporting R&D starters in most sectors, while the relationship is reversed for highly capital-intensive sectors, such as tobacco and petroleum exploration. One possible explanation is that exporting lowers the threshold for conducting R&D and the effect is more manifest in labor-intensive sectors.

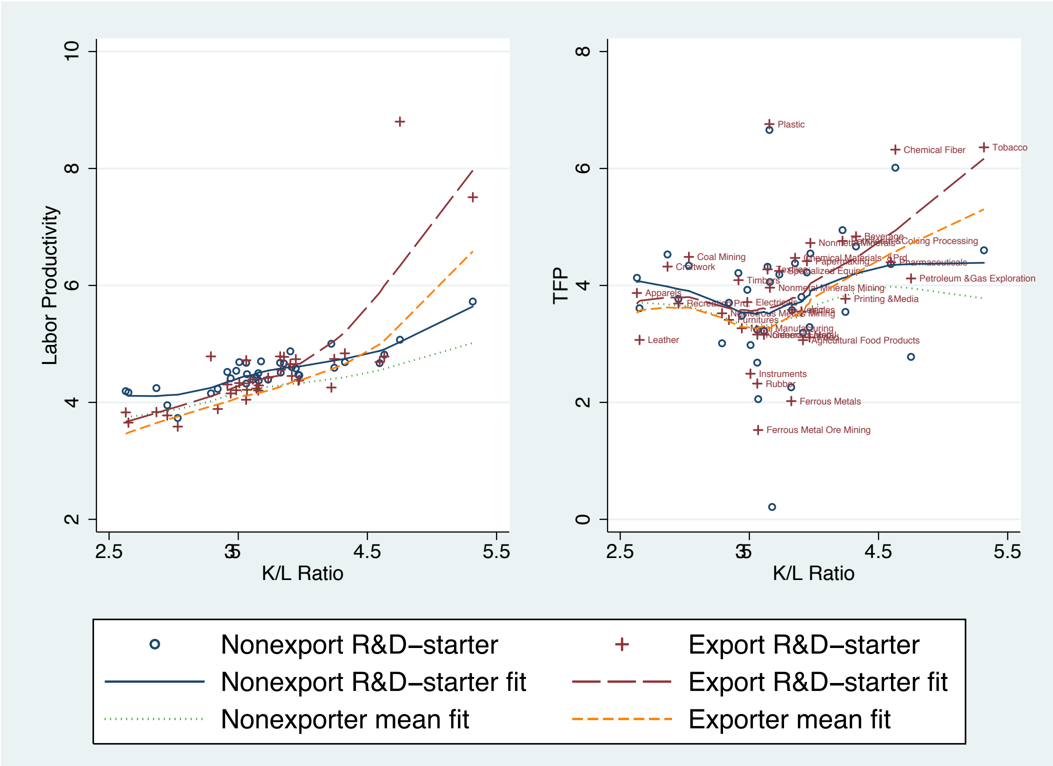


Figure 3.2: Productivity of R&D Starters Conditional on Exporting Status

Notes: TFP is estimated using the method of Olley and Pakes (1996). A log-linear smooth fit is utilized for illustrating the trend. K/L ratio is the median level of capital-labor ratio within each industry.

In labor-intensive sectors, the average productivity of exporters is lower than that of non-exporters while the reverse trend presents in capital-intensive sectors; this can be seen by comparing the log-linear fit of mean productivity for non-exporters and exporters. As before, the relative relationship among R&D starters, exporters and nonexporters, in terms of LP and TFP is quite similar.

Although exporters are not necessarily more productive than non-exporters, especially in labor-intensive sectors, and R&D investors are instead more productive, the fraction of R&D investors among exporters is actually higher than the fraction among nonexporters in most sectors except for instrument and leather, as shown in Figure 3.3. One conjecture might be that the activ-

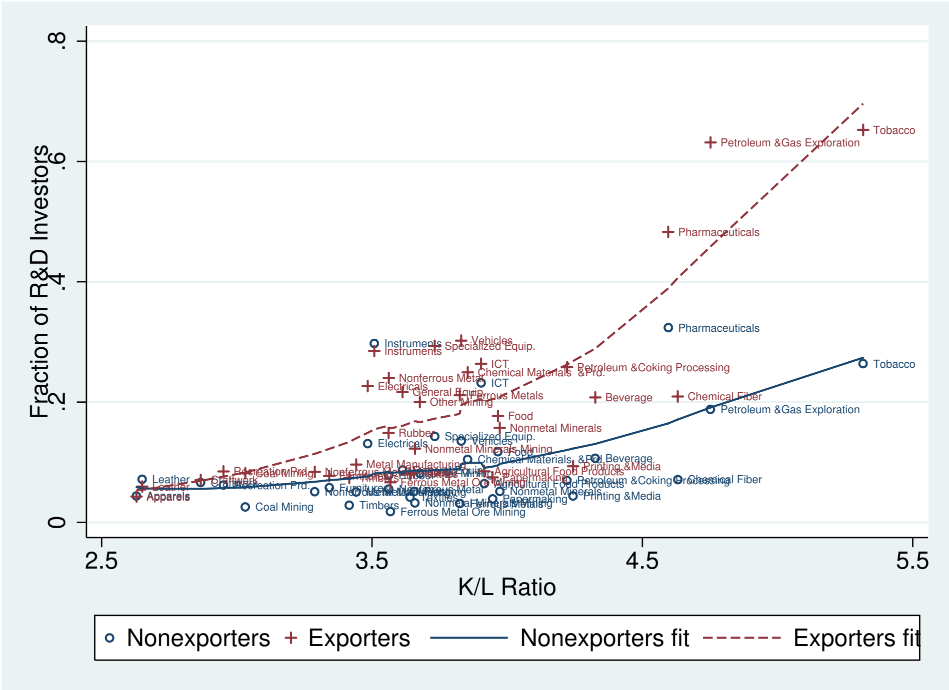


Figure 3.3: Fraction of R&D Investors among Exporters and Non-exporters
Notes: A log-linear smooth fit is utilized for illustrating the trend. K/L ratio is the median level of capital-labor ratio at each industry.

ity of exporting increases the tendency for firms to invest in R&D. Additionally, the fraction of R&D investors tends to increase in line with a sector's capital-intensity.

3.3.3 The divergent performance from the decisions of firms

The average productivity for the four decision groups, i.e. non-exporters with or without R&D investment, exporters with or without R&D investment, is plotted in Figure 3.4. The comparison of Figure 3.2 and 3.4 indicates a certain complementarity between the impact of the decision to export and invest in R&D on improving the productivity of firms. This can be concluded given the fact that those exporting firms that invest in R&D show

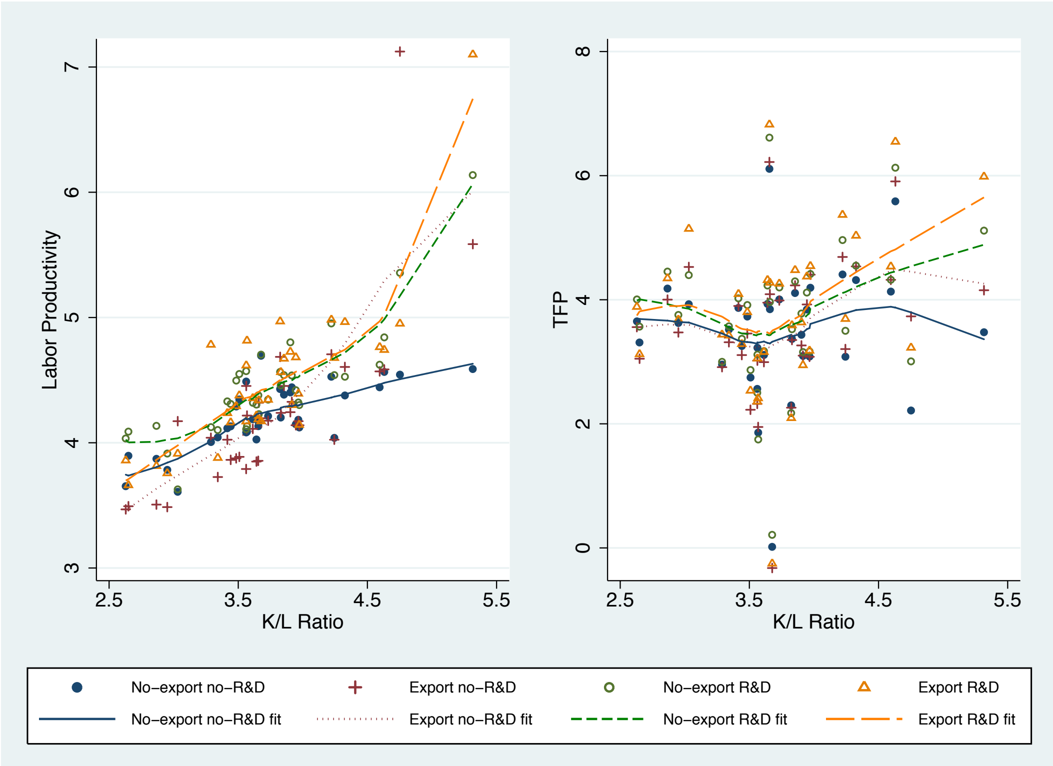


Figure 3.4: Productivity and Firms' Decision across Sectors

Notes: A log-linear smooth fit is utilized for illustrating the trend. K/L ratio is the median level of capital-labor ratio at each industry.

the best performance in more sectors than the situation in figure 3.2 where the performance of R&D starters are illustrated, especially in terms of TFP. Exporting firms that do not invest in R&D show the worst performance in more labor-intensive sectors. On the contrary, the performance of R&D investors is significantly better than that of non-R&D-investors, among both exporters and non-exporters.

As an alternative evidence that relates the capital-labor characteristics to the performance of firms and their decisions, firms are pooled together and grouped into 100 bins based on their K/L ratio. The average profits (value-added), LP and TFP for each of the four groups are plotted in relation to their K/L bins in Figure 3.5. Exporting firms that invest in R&D exhibit the highest profits along all bins, followed by their non-exporting counterparts.

Non-exporters without R&D investment display the lowest level of profits.

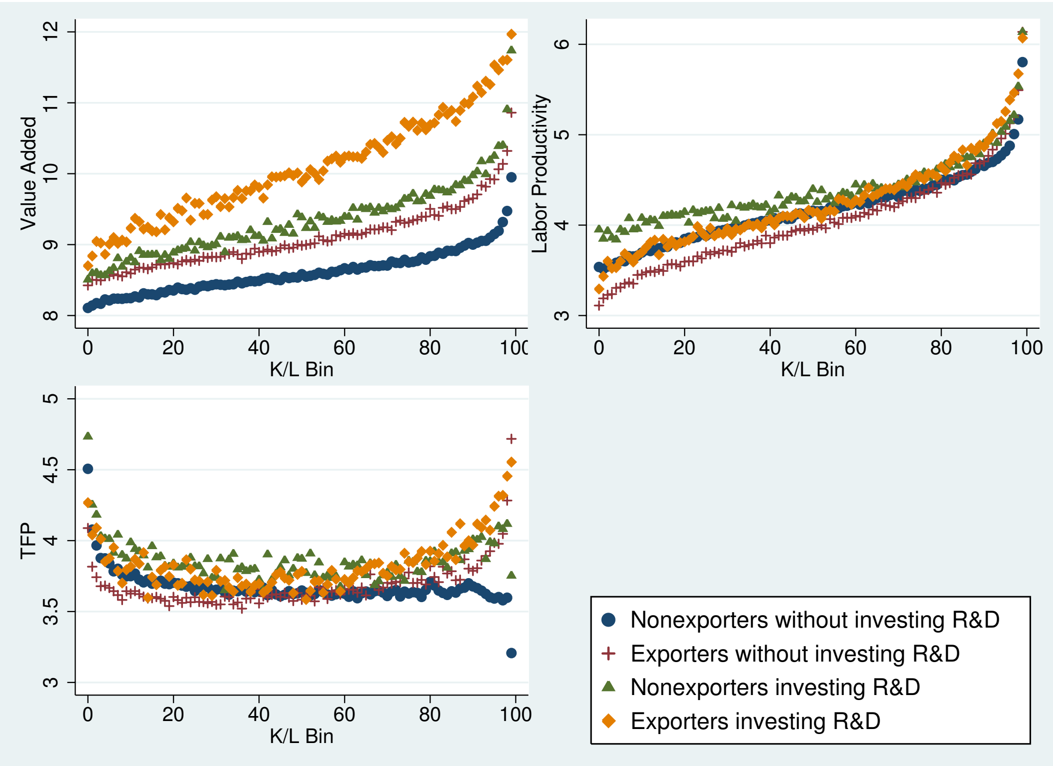


Figure 3.5: Profits and Productivity among R&D Investors and Exporters
Notes: Firms are grouped into 100 bins according to their capital-labor (K/L) ratio.

However, exporters that invest in R&D do not experience monotonically dominant position in terms of productivity compared to other three groups. In labor-intensive bins (i.e. the lower K/L bins), exporting R&D investors are less productive than their non-exporting counterparts, while the situation is reversed in capital-intensive bins. This suggests that exporters in labor-intensive bins achieve the higher profits by hiring more employees than non-exporters. Furthermore, R&D investors are superior to firms that do not invest in any R&D in terms of LP and TFP within both exporting and non-exporting groups.

To summarize, the K/L characteristics of a sector are relevant for the export decision of firms and its interaction with R&D investment. In the context of China, the decision of firms to export and invest in R&D differs systematically between labor- and capital intensive sectors. Better-performing firms tend to conduct R&D due to their initially higher levels of productivity. These findings are explained by a hybrid model proposed in the following section.

3.4 Model

I first introduce the R&D decision of firms to Melitz's (2003) model in the similar manner to that of Bustos (2011) under the autarky with two production factors (See Appendix B.2.1 for the autarky model). Then, in an open-economy setting, factor endowments are added to the model in an analogous fashion to Bernard et al. (2007b). Firms are heterogeneous regarding on both different levels of productivity and their corresponding decisions.

Two countries, H and F, are asymmetric in terms of production factors, i.e, capital K and labor L, with the home country H relatively labor abundant: $\frac{K^H}{L^H} < \frac{K^F}{L^F}$. The returns on a given factor follow $\frac{w^H}{r^H} < \frac{w^F}{r^F}$, where w denotes the wage and r denotes the rent. This setup can be considered as the case of China (H) and the U.S. (F). Two sectors are different in the factor intensity for both countries.

Preference

For simplicity, I drop the country index where it does not create ambiguity. The CES utility function in sector i is an integral of quantities q_i over a continuum of varieties of goods, indexed by ω,

$$U_i = [\int_{\omega \in \Omega_i} q_i(\omega)^{\rho} \mathrm{d}\omega]$$

where $\rho = 1 - \frac{1}{\sigma}$, with $0 < \rho < 1$ and $\sigma > 1$. σ is the elasticity of substitution across all varieties, which is the same for all sectors and countries.

The overall utility can be expressed as:

$$U = \prod_{i \in I} (U_i)^{\alpha_i}$$

with $\alpha_i \in (0, 1)$ the share of spending on sector i. It is the same for both countries.

The budget constraint for the whole economy can be written as:

$$\int_{i \in I} \int_{\omega_i \in \Omega} p(\omega) q(\omega) \mathrm{d}\omega \mathrm{d}i = B$$

which is also the same for both countries, implying the respective markets are of equal size.

The aggregate price index in sector i is

$$P_i = [\int_{\omega \in \Omega_i} p_i(\omega)^{1-\sigma} d\omega]^{\frac{1}{1-\sigma}}$$

The demand for a particular variety is,

$$q_i^{\omega} = \alpha_i B P_i^{\sigma-1} p_i^{-\sigma}(\omega) \tag{3.1}$$

Supply

The market structure faced by producers is the monopolistic competition. Firms are heterogeneous in their productivities φ in each sector. Two countries, H and F, engage in a frictional trade. Firms in each of the sectors in both countries are assumed to follow the same *ex ante* productivity distribution.

(1) Firms enter the market by paying a fixed entry cost $f_{i,e}$ unit to learn their productivity, the result of which is drawn from a known Pareto distri-

bution function.[2]

$$G(\varphi) = 1 - \varphi^{-s}, \quad s > \sigma - 1$$

If a firm's productivity is lower than the exit productivity cutoff, $\varphi < \varphi^*$, then the firm exits. Conditional on firms' survival, the distribution of the productivity is:

$$\mu(\varphi) = \begin{cases} \frac{g(\varphi)}{1-G(\varphi^*)} & \text{if } \varphi \geqslant \varphi^* \\ 0 & \text{otherwise} \end{cases}$$

The production function for a firm with productivity φ in sector i is:

$$y_i(\varphi) = \varphi l^{\theta_i} k^{1-\theta_i}$$

where θ_i is the labor intensity of sector i, the same for both countries. Sector i is more labor intensive than sector j if $\theta_i > \theta_j$ $(i \neq j)$.

At this point, firms decide whether to export or to invest in R&D.

(2) Firms decide to pay a fixed cost $f_{i,r}$ unit ($f_{i,r} > 0$) to invest R&D activities in order to decrease the marginal cost or increase the productivity by λ_i. Given a certain amount of $f_{i,r}$, the magnitude of λ_i reflects a sector's technological opportunities and appropriabilities. Higher technological opportunities and appropriabilities correspond to a bigger λ_i.

(3) Firms decide to pay a fixed cost $f_{i,x}$ unit ($f_{i,x} > 0$) in order to enter the foreign market.

The production cost consists of the fixed cost needed to engage in production, or to undertake R&D investment, or to begin exporting, plus the additional marginal cost. Firm costs under different R&D decision ($D = \{0, 1\}$)

[2] In principle, it could be a more general distribution function. A Pareto distribution is assumed for analytical convenience because, under the CES demand system, the relevant variables which are the power of firm's productivity, such as revenue, profit and demand, are also Pareto distributed.

are given by,

$$c_i(\varphi) = \begin{cases} [f_i + \frac{q(\varphi)}{\varphi}]w^{\theta_i}r^{1-\theta_i} & \text{if } \{D\} = 0 \\ [f_i + f_{i,r} + \frac{q(\varphi)}{\lambda_i \cdot \varphi}]w^{\theta_i}r^{1-\theta_i} & \text{if } \{D\} = 1 \end{cases} \tag{3.2}$$

The price is the markup over the marginal cost $p_i(\varphi) = \frac{w^{\theta_i}r^{1-\theta_i}}{\rho \cdot \varphi}$. Firms with productivity φ are able to sell $q_i(\varphi) = \alpha_i B P_i^{\sigma-1}(\rho\varphi)^{\sigma}(w^{\theta_i}r^{1-\theta_i})^{-\sigma}$, according to the demand function specified in (3.1). If firms invest in R&D, they will be able to charge a lower price $p_{i,r}(\varphi) = \frac{w^{\theta_i}r^{1-\theta_i}}{\lambda_i \cdot \rho\varphi}$ and sell more $q_{i,r}(\varphi) = \alpha_i B P_i^{\sigma-1}(\rho\varphi \cdot \lambda_i)^{\sigma}(w^{\theta_i}r^{1-\theta_i})^{-\sigma}$. Under the assumption that the fixed cost of R&D investment is the same across firms, the more productive firms with a higher φ benefit more from R&D investment. If firms choose to export, there is an ice-berg cost τ ($\tau > 1$) for each unit of exporting product. Therefore, the price in the foreign market is adjusted to the trade cost, which yields $p_{i,x}(\varphi) = \tau p_i(\varphi)$.

Profit Maximization

Conditional on the observed productivity φ, firms maximize their profits by choosing to invest in R&D ($D = \{0, 1\}$) and/or export ($X = \{0, 1\}$). The potential profit can be written in terms of the cost function specified as equation (3.2) and pricing rule:

$$\pi_i^H(\varphi) = \begin{cases} \frac{\alpha_i}{\sigma}B[\frac{P_i^H\rho}{m_i^H}\varphi]^{\sigma-1} - f_i m_i^H & \text{if } \{D, X\} = (0,0) \\ \frac{\alpha_i}{\sigma}B[\frac{P_i^H\rho}{m_i^H}\lambda_i\varphi]^{\sigma-1} - (f_i + f_{i,r})m_i^H & \text{if } \{D, X\} = (1,0) \\ \frac{\alpha_i}{\sigma}B[\frac{P_i^F\rho}{\tau m_i^H}\varphi]^{\sigma-1} + \frac{\alpha_i}{\sigma}B[\frac{P_i^H\rho}{m_i^H}\varphi]^{\sigma-1} - (f_i + f_{i,x})m_i^H & \text{if } \{D, X\} = (0,1) \\ \frac{\alpha_i}{\sigma}B[\frac{P_i^F\rho}{\tau m_i^H}\lambda_i\varphi]^{\sigma-1} + \frac{\alpha_i}{\sigma}B[\frac{P_i^H\rho}{m_i^H}\lambda_i\varphi]^{\sigma-1} - (f_i + f_{i,x} + f_{i,r})m_i^H & \text{if } \{D, X\} = (1,1) \end{cases} \tag{3.3}$$

where $m_i^H = w^{H\theta_i}r^{H(1-\theta_i)}$ and P_i^F is the price index for sector i in the foreign market.

Productivity Cutoffs

Firms make their decisions by comparing the potential profits from various decisions. These different possibilities generate four cutoff points along productivity range of firms. The exit productivity cutoff φ_i^{*H} identifies the lowest level of productivity for survival firms, determined by

$$\pi_i^H\{0,0;\varphi_i^{*H}\} = 0 \iff \varphi_i^{*H} = \frac{m_i^H}{\rho P_i^H}(\frac{\sigma f m_i^H}{\alpha_i B})^{\frac{1}{\sigma-1}}$$

The export cutoff productivity or the level of firms productivity causing firms to export $\varphi_{i,x}^H$ is determined under the condition that the marginal exporter's profit is indifferent between exporting and non-exporting.

$$\pi_i^H\{0,1;\varphi_{i,x}^H\} = \pi_i^H\{0,0;\varphi_{i,x}^H\} \iff \varphi_{i,x}^H = \frac{\tau m_i^H}{\rho P_i^F}(\frac{\sigma f_{i,x} m_i^H}{\alpha_i B})^{\frac{1}{\sigma-1}}$$

The R&D-investing productivity cutoff in sector i $\varphi_{i,r}$ is the productivity that makes the profits of doing R&D indifferent with that of no-R&D-investing.

$$\pi_i\{1,0;\varphi_{i,r}^H\} = \pi_i\{0,0;\varphi_{i,r}^H\} \iff \varphi_{i,r} = \frac{m_i^H}{\rho P_i^H}[\frac{\sigma f_{i,r} m_i^H}{(\lambda_i^{\sigma-1}-1)\alpha_i B}]^{\frac{1}{\sigma-1}}$$

The R&D-investing and export productivity cutoff is given by

$$\pi_i^H\{1,1;\varphi_{i,x}^H\} = \pi_i^H\{0,0;\varphi_{i,x}^H\} \iff \varphi_{i,xr}^H = [\frac{\sigma(f_{i,x}+f_{i,r})m_i^H}{\alpha_i B[(\lambda_i^{\sigma-1}-1)(P_i^H)^{\sigma-1} + (\frac{\lambda_i}{\tau}P_i^F)^{\sigma-1}]}]^{\frac{1}{\sigma-1}}\frac{m_i^H}{\rho}$$

The export productivity cutoff can be expressed as the exit cutoff productivity as follows

$$\frac{\varphi_{i,x}^H}{\varphi_i^{*H}} = \tau(\frac{f_{i,x}}{f_i})^{\frac{1}{\sigma-1}}\frac{P_i^H}{P_i^F}$$

When $\frac{P_i^F}{P_i^H} = 1$, the model falls into the world of Melitz (2003) where countries are symmetric and exporters will sell their products to all countries. The result is exactly what Melitz (2003) derives. More productive firms choose to export whenever $\tau(\frac{f_{i,x}}{f_i})^{\frac{1}{\sigma-1}} > 1$.

However, when countries are asymmetric with respect to factor prices, the ratio of the cutoff productivity between foreign market entry and domestic market entry, $\frac{\varphi^H_{i,x}}{\varphi^{*H}_i}$, decreases in relation to the relative price index between foreign and home countries, $\frac{P^F_i}{P^H_i}$, *ceteris paribus.* As shown in Figure 3.6, when the relative price between foreign and domestic market is larger than $\tau(\frac{f_{i,x}}{f_i})^{\frac{1}{\sigma-1}}$, the export productivity cutoff is lower than the exit productivity cutoff level. In this case, it is not necessary that more productive firms export in those sectors.

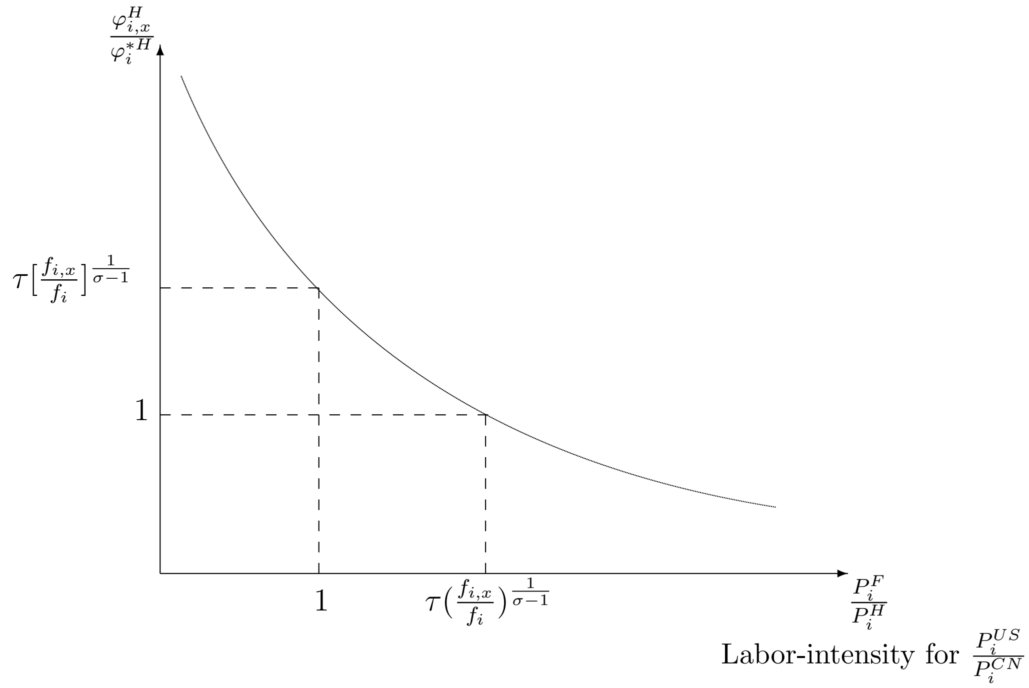


Figure 3.6: Relative Price and Productivity Cutoffs for Market Entry

Considering the case of China and the US, intuitively $\frac{P^F_i}{P^H_i}$ increases as a result of the sector's labor-intensity θ_i (See Proposition 1 for the proof after the full model is presented). This leads to the prediction that the export productivity cutoff is theoretically lower than domestic market entry in more labor-intensive sectors in China where foreign market does not have the selection function for Chinese firms. Consequently, it is likely that the less productive firms in these labor-intensive sectors will export.

Domestic-oriented firms can achieve more profits relative to exporters through investing in R&D. The theoretical ratio of non-exporters' R&D productivity cutoff $\varphi_{i,r}^{H}$ to the export productivity cutoff, $\varphi_{i,x}^{H}$, is proportional to $\frac{P_i^F}{P_i^H}$, expressed as follows:

$$\frac{\varphi_{i,r}^{H}}{\varphi_{i,x}^{H}} = \tau[\frac{f_{i,r}}{f_{i,x}(\lambda_i^{\sigma-1} - 1)}]^{\frac{1}{\sigma-1}} \frac{P_i^F}{P_i^H}$$

In those sectors where the export productivity cutoff is lower than the exit productivity cutoff, i.e., $\frac{P_i^F}{P_i^H} > \tau(\frac{f_{i,x}}{f_i})^{\frac{1}{\sigma-1}}$, the R&D investment cutoff productivity would be larger than the export productivity cutoff, *ceteris paribus*. Consequently, domestic R&D investors will show higher productivity than exporters in such sectors, as shown in Figure 3.2.

When firms make their decisions in a single step, the exporting-R&D productivity cutoff will always be larger than the domestic R&D-investing productivity cutoff or the export productivity cutoff for all sectors. Sectors are divided into two types based on the above analysis. When the relative price index between foreign and home countries is larger than $\tau(\frac{f_{i,x}}{f_i})^{\frac{1}{\sigma-1}}$, less productive firms export, more productive firms conduct R&D and serve domestic market, and most productive firms do both. When the relative price index between foreign and home countries is smaller than $\tau(\frac{f_{i,x}}{f_i})^{\frac{1}{\sigma-1}}$, more productive firms export while less productive firms serve the domestic market. Among either exporters or nonexporters, the relatively more productive firms conduct R&D.

The decision to invest in R&D conditional on exporting status

However, firms might make their decisions in two steps. First, they decide whether to export. Next, they decide whether to conduct R&D. The R&D-

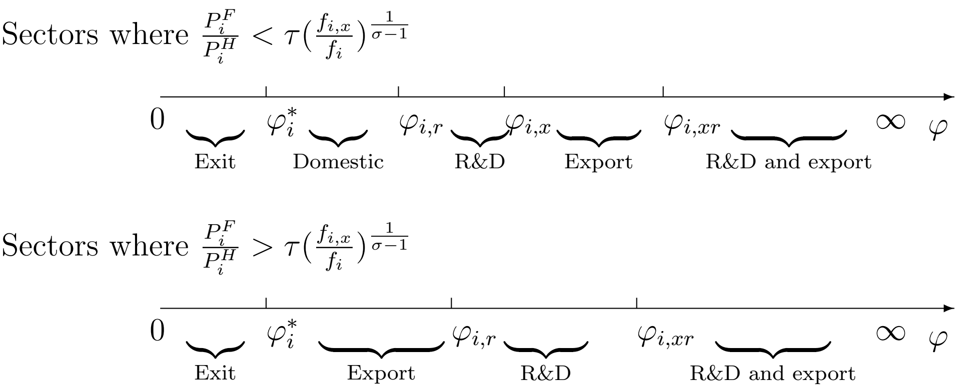


Figure 3.7: Productivity Cutoffs in the Open Economy

investing productivity cutoff for exporters, $\varphi_{i,r|x=1}$, is then determined by

$$\pi_i^H\{1,1;\varphi^H_{i,r|x=1}\} = \pi_i^H\{0,1;\varphi^H_{i,r|x=1}\} \iff \varphi^H_{i,r|x=1} = \frac{m_i^H}{\rho}\left[\frac{\sigma f_{i,r} m_i^H}{\alpha_i B(\lambda_i^{\sigma-1}-1)[(\frac{P_i^F}{\tau})^{\sigma-1}+(P_i^H)^{\sigma-1}]}\right]^{\frac{1}{\sigma-1}}$$

The ratio of R&D-investing cutoff productivity between exporters and domestic-oriented firms is therefore proportional to the relative price indices of the various sectors for the trading countries.

$$\frac{\varphi^H_{i,r|x=1}}{\varphi^H_{i,r|x=0}} = \left[\frac{1}{(\frac{P_i^F}{\tau P_i^H})^{\sigma-1}+1}\right]^{\frac{1}{\sigma-1}} < 1$$

Trade liberalization lowers the threshold necessary to invest in R&D for exporters compared to domestic-oriented firms. The result holds for both the assumption of symmetric countries and asymmetric countries. When countries are asymmetric, the effect is more obvious in comparative advantage sectors because $\frac{P_i^F}{P_i^H}$ is relatively larger for those sectors. Non-exporters basically have a higher threshold to become the R&D investors. This argument explains why non-exporting firms starting to conduct R&D generally have higher level of productivity than their exporting counterparts, especially in labor-intensive sectors in China, as shown in Figure 3.2 of section 3.3.

Determinants of equilibrium

Free entry (FE), zero cutoff profit (ZCP), and the balance of payment conditions are used to solve the equilibrium, as expressed in equation (3.4). FE condition implies that the present value of expected profits needs to equal the sunk entry cost. ZCP condition states that the average level of profits at the exit productivity cutoff φ_i^{*H} is equal to zero. Firms with the productivity level lower than the cutoff φ_i^{*H} will generate negative profits and exit the market. The balance of payment condition requires the value of total exports of one country to be equal to that of the other country.

$$\begin{aligned}&f_{i,e}m_i^H = [1 - G(\varphi^* H)]\tfrac{1}{\delta}\bar{\pi}_i^H \quad (FE)\\ &\pi_i^H(\varphi_i^{*H}) = \tfrac{1}{\sigma}\alpha_i B(\tfrac{P_i\rho}{m_i^H})^{\sigma-1}(\varphi^{*H})^{\sigma-1} - f_i m_i^H = 0 \quad (ZCP)\\ &R_{1x}^H + R_{2x}^H = R_{1x}^F + R_{2x}^F\end{aligned} \tag{3.4}$$

Under the steady state, a firm's productivity remains constant, therefore, each firm's expected value function over time is given by

$$v(\varphi) = max\{0, \sum_{t=0}^{\infty}(1-\delta)^t\pi(\varphi)\} = max\{0, \frac{1}{\delta}\pi(\varphi)\} \tag{3.5}$$

The *ex post* expected profit $\bar{\pi}_i^H$ is the sum of both the expected domestic profit $\bar{\pi}_{id}^H$ and the expected exporting profit $\bar{\pi}_{ix}^H$,

$$\bar{\pi}_i^H = \bar{\pi}_{id}^H(\tilde{\varphi}_{id}^H) + prob_{ix}^H\bar{\pi}_{ix}^H(\tilde{\varphi}_{ix}^H)$$

where $prob_{ix}^H = \frac{1-G(\varphi_{i,x}^H)}{1-G(\varphi^{*H})}$ is the probability of firms exporting in sector i.

$$\bar{\pi}_{ix}^H(\tilde{\varphi}_{ix}) = \frac{\alpha_i B}{\sigma}(\frac{P_i^F\rho}{\tau m_i^H})^{\sigma-1}[\tilde{\varphi}_{ix}(\varphi_i^{*H})]^{1-\sigma} - f_{ix}m_i^H \tag{3.6}$$

The *ex post* expected level of export productivity $\tilde{\varphi}_{ix}^H$ can be written as the exit cutoff productivity φ_i^{*H} and relative price index P_i^H/P_i^F, using a one-step decision cutoff.

$$\tilde{\varphi}_{ix}^{H} = [\int_{max\{\varphi_{i,x}^{H},\varphi^{*H}\}}^{\varphi_{i,xr}^{H}} \varphi^{\sigma-1}\frac{g(\varphi)}{1-G(\varphi^{*H})}\mathrm{d}\varphi + \int_{\varphi_{i,xr}^{H}}^{\infty}(\lambda_i\varphi)^{\sigma-1}\frac{g(\varphi)}{1-G(\varphi_{i,xr}^{H})}\mathrm{d}\varphi]^{\frac{1}{\sigma-1}} \tag{3.7}$$

Aggregation

Factor demand in sector i is

$$r^H K_i^H = \frac{1-\theta_i}{\theta_i} w^H L_i^H, \quad R_i^H = \frac{(1-\theta_j)w^H L^H - \theta_j r^H K^H}{\theta_i - \theta_j} \tag{3.8}$$

See Appendix B.2.2 for the derivation of the factor demand condition.

The sum of domestic and foreign expenditures on domestic varieties equals the value of domestic production (i.e. total industry revenue R_i^H) for each sector and country. Goods market clearance implies that consumers' expenditure in sector i are equal in both countries.

$$R_{id}^H + R_{ix}^F = R_{id}^F + R_{ix}^H$$

The number of firms in sector i is given by

$$N_i^H = \frac{R_i^H}{\bar{r}} = \frac{w^H L_i + r^H K_i}{\sigma(\bar{\pi} + f_{i,e} + prob_x n f_{i,x} m_i^H)}$$

The aggregate price index is

$$P_i^H = \frac{1}{\rho}[N_i^H(\tilde{\varphi}_{id}^H)^{\sigma-1} m_i^H + N_{ix}^F(\tau^{-1}\tilde{\varphi}_{ix}^F)^{\sigma-1} m_i^F]^{\frac{1}{1-\sigma}}$$

Proposition 1. *The relative price index for the two countries increases in a sector of domestic comparative advantage. If $\theta_1 > \theta_2$ and $\frac{w^H}{r^H} < \frac{w^F}{r^F}$, then $\frac{P_1^F}{P_1^H} > \frac{P_2^F}{P_2^H}$.*

See Appendix B.2.3 for the proof.

3.4.1 Complementarity between R&D investment and exporting

Proposition 2. *The decision of firms to invest in R&D and export has a complementary impact on the profits of firms.*

Proof. The existence of a complementarity between R&D investment and exporting on the profitability of firms is proved by using supermodularity theory.

Definition 1. *The function* $f : \mathbf{R^k} \to \mathbf{R}$ *is supermodular if*

$$f(x \vee y) + f(x \wedge y) \geqslant f(x) + f(y)$$

for all $x, y \in \mathbf{R^k}$*, where* $x \vee y$ *denotes the component-wise maximum and* $x \wedge y$ *the component-wise minimum of* x *and* y*.*

If function f is smooth, the supermodularity is equivalent to the condition (Milgrom and Roberts, 1990),

$$\frac{\partial^2 f}{\partial z_i \partial z_j} \geqslant 0 \quad \textit{for all } i \neq j$$

$\pi(\cdot)$ is smooth because as a function of $\tilde{\varphi}$, the profit function is Pareto distributed, and because the profit cutoff mechanism guarantees marginal firms on two sides of each decision border have the continuous profits value[3]. Therefore, if equation (3.9) is fulfilled, R&D investment and exporting will have a complementary effect on the profits of firms.

$$\pi_i^H\{1,1;\varphi\} + \pi_i^H\{0,0;\varphi\} \geqslant \pi_i^H\{0,1;\varphi\} + \pi_i^H\{1,0;\varphi\} \tag{3.9}$$

[3]On the contrary, the revenue function has a jump at the cutoff point owing to the fact that exporters or R&D investors need to generate a discontinuous boost of revenue in order to compensate for the fixed costs of investing; the similar idea is demonstrated in Melitz (2003).

This result is equivalent to $\frac{\alpha_i B}{\sigma}(\frac{P_i^F}{\tau m_i^H}\varphi_i)^{\sigma-1}(\lambda_i^{\sigma-1}-1) \geqslant 0$, derived from the profit function (3.3). Note that $\lambda_i > 1$, the above equation comes into existence. □

In conjunction with the lower threshold of R&D-investing for exporters, this proposition helps to explain why the fraction of R&D investors among exporters is higher in China than that of nonexporters. In fact, according to Proposition 2, exporters with R&D investment are supposed to generate the highest profits over any of the groups, as shown in Figure 3.5.

3.4.2 Discussion

Note that when the export productivity cutoff is not able to partition firms in a certain sector, all firms in home country H would export labor-intensive goods as long as R&D investment and the differences in technology are not included in the model. As a result, this leads to the complete specialization towards comparative advantage sectors, as H-O theory predicts. The model of Bernard et al. (2007b) rules out this possibility by restricting the export cutoff productivity to a level higher than the exit cutoff for both sectors. For the model in this chapter, however, R&D investment brings higher productivity and consequently a larger domestic market share for firms in comparative advantage sectors. Moreover, the higher productivity through R&D investment makes the exporting of goods in sectors without comparative advantages not only possible but also profitable. Hence, in order to export capital-intensive goods, exporters would need to be very productive in home country, as illustrated in Figure 3.1 for the case of China.

3.5 Econometric Models and Results

In this section, the complementary of the decisions to export and invest in R&D from Chinese manufacturing firms is further investigated under the guideline of the above model. I first analyze the relationship between firm productivity and their decisions to export or invest in R&D using OLS specification over a pooled sample, as well as separate regressions restricted to the labor- and capital-intensive sectors respectively. Then, I analyze the complementarity with respect to the export decision or the R&D decision using a separate Probit regression. In both cases, structural break test is utilized to examine whether a separate regression is appropriate and statistically significant. Finally, I use multinomial treatment model to estimate any potential complementarity between the decisions to invest in R&D and export on firm productivity through disentangling the self-selection bias from the post-decision effect.

3.5.1 Productivity and firm decision: pooled OLS

The relationship between firm productivity and their decision to export and/or R&D investment is investigated using equation (3.10). The dependent variables, y_i, is either LP or TFP. Since TFP is estimated residual of a regression using capital and labor as explanatory variables, a two-step regression of TFP on a list of variables may generate inconsistent estimators. Consequently, the TFP regression serves only as a reference in the following analysis. The main result comes from LP regression. Except for decision variables, such as the export dummy (*export*), the R&D dummy (*R&D*), and their interaction term ($EXP * R\&D$), the control variable set $\mathbf{x_i}$ includes the number of employees, capital-labor ratio, wages per worker, the ownership dummy, the industry dummy and the year dummy. Four types of firms are differentiated through the ownership dummy. They are state-owned firms, non-state-owned indigenous firms, foreign-owned firms or Hong Kong-, Taiwanese- or Macao-owned firms (HTM). Two regressions for labor- and capital-intensive sectors are estimated separately. The devision point for labor-intensive sectors occurs where the median capital-labor ratio (MK/L) is equal to 4. A Chow test is applied to compare whether the coefficients beween labor- and capital-intensive sectors are significantly different in order to confirm whether a structural break exists between these sectors. To clarify, a Chow test is essentially the F test on the equality of pooled estimators.

$$y_i = \beta_e export_i + \beta_r R\&D_i + \beta_{er} EXP * R\&D_i + \beta \mathbf{x_i} + \epsilon_i \tag{3.10}$$

As can be seen from Table 3.3, the sign and magnitude of LP and TFP estimators within each sample category are quite similar, with the exception of K/L and $(K/L)^2$. This difference reflects the conceptual distinction between LP and TFP. Unlike the monotonic relationship between LP and K/L, there is a U-shaped relationship between TFP and the K/L ratio. This is consistent with figures in Section 3.3, which reveal a quite similar relationship between the various decision groups for LP and TFP. Additionally, a Chow test rejects the null hypothesis significantly, therefore, confirming a different pattern between labor- and capital-intensive sectors.

The estimators over the pooled sample are quite similar to the estimators for the labor-intensive sectors because the MK/L cutoff at 4 partitions most of the sectors as labor-intensive. This results in much more observations in the labor-intensive regression than in the capital-intensive regression. Accordingly, this division gives more weight for labor-intensive results in the pooled estimation.

Moreover, the exporting status is negatively correlated with productivity in both the labor-intensive sectors and the pooled samples, while investing R&D has a significantly positive effect on productivity in each regression. The interaction term of R&D and export shows a positive sign for both LP and TFP in the labor-intensive regression, but not significant in the capital-intensive regression. In labor-intensive sectors, exporters that invest in R&D attain 16 percent higher level of productivity. Not surprisingly, the number of employees is negatively correlated with productivity. Higher wage has a positive effect on productivity, which can be interpreted as more skilled

Table 3.3: Productivity and Firm Decision: OLS Regression

	Labor Productivity			TFP		
	Pooled	Labor-intensive	Capital-intensive	Pooled	Labor-intensive	Capital-intensive
export	-0.088***	-0.087***	0.022	-0.090***	-0.087***	0.023
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
R&D	0.139***	0.137***	0.123***	0.138***	0.139***	0.102***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
EXP*R&D	0.096***	0.111***	-0.043	0.069***	0.076***	0.002
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
K/L	0.234***	0.229***	0.271***	-0.226***	-0.236***	-0.249***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
labor	-0.668***	-0.658***	-0.737***	-0.496***	-0.495***	-0.474***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
avwage	0.509***	0.487***	0.657***	0.488***	0.469***	0.607***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
non-state-owned	0.631***	0.650***	0.557***	0.592***	0.654***	0.473***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
foreign	0.625***	0.647***	0.579***	0.574***	0.634***	0.527***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
HTM	0.467***	0.485***	0.458***	0.424***	0.485***	0.390***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
$(K/L)^2$				0.022***	0.024***	0.020***
				(0.00)	(0.00)	(0.00)
constant	2.004***	2.105***	1.751***	2.845***	2.926***	0.335***
	(0.01)	(0.01)	(0.06)	(0.01)	(0.01)	(0.06)
industry	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
N	886,447	809,862	76,585	886,447	809,862	76,585
R^2	0.297	0.283	0.414	0.460	0.442	0.604
Chow Test	133.36 (p=0.00)			2.28 (p=0.10)		

*Notes: Robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The devision point of K/L ratio for labor- and capital-intensive sectors is 4. The Chow test is F test on the equality of coefficients in two separate regressions. "HTM" refers to Hong Kong-, Taiwanese- or Macao-owned firms.*

workers contribute positively to productivity.

3.5.2 Decisions of firms: presence of a structural break across sectors

In this section, the decisions of firms to export or invest in R&D are estimated separately using a Probit regression. The control variable set $\mathbf{x_i}$ includes the same variables as the OLS specification. The median level of capital-labor ratio (MK/L) and the R&D dummy are included in the export-decision regression, while the export dummy (*export*) and the median capital-labor ratio (MK/L) are included in the R&D decision regression. Both the preliminary analysis in Section 3.3 and the proposed model in Section 3.4 suggest that a sector's factor requirement is an important determinant on the decision of firms to export and invest in R&D. Again, two regressions for labor- or capital-intensive sectors are estimated separately, with division point at 4 of the MK/L. Robustness standard errors are applied to correct for heteroscedasticity. Results are shown in Table 3.4.

$$Pr(export|\mathbf{X}) = \Phi(\beta\mathbf{x_i} + \beta R\&D_i + \beta MK/L_i)$$
$$Pr(R\&D|\mathbf{X}) = \Phi(\beta\mathbf{x_i} + \beta export_i + INV_i)$$

A structural break test is needed to examine whether the separate regressions are statistically significant. For the non-linear discret choice model, an F test is not valid for examining the structure break as Allison (1999) points out a Chow test tells nothing about the underlying impact of explanatory variables for two groups in discrete choice models because their coefficients are not directly identified. Therefore the comparison of two logit or probit regression requires a series of test with stricter assumption on the variation of the residual. Using a Monte Carlo simulation, Hoetker (2007) confirms the identification problem a Chow-type test may cause is relevant for testing discrete choice models and proposes a series of alternative tests, which this

Table 3.4: Decisions of Firms: Probit Regression

	Export Decision			R&D Decision		
	Pooled	Labor-intensive	Capital-intensive	Pooled	Labor-intensive	Capital-intensive
lagTFP	-0.067***	-0.071***	0.010	0.108***	0.110***	0.091***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.03)
R&D	0.258***	0.264***	0.208***			
	(0.01)	(0.01)	(0.02)			
export				0.262***	0.270***	0.198**
				(0.02)	(0.02)	(0.06)
investment				0.044***	0.045***	0.034**
				(0.00)	(0.00)	(0.01)
MK/L	0.107	0.366***	-1.985***	-0.468***	-4.524***	0.399
	(0.10)	(0.10)	(0.32)	(0.08)	(0.51)	(0.29)
K/L	-0.052***	-0.052***	-0.036***	0.073***	0.070***	0.098***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
labor	0.311***	0.314***	0.259***	0.309***	0.305***	0.336***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
avwage	0.203***	0.204***	0.194***	0.353***	0.359***	0.322***
	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.04)
non-state-owned	0.331***	0.359***	0.204***	-0.095***	-0.105***	-0.060
	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.06)
foreign	1.383***	1.431***	0.910***	-0.418***	-0.439***	-0.294**
	(0.01)	(0.02)	(0.04)	(0.04)	(0.04)	(0.11)
HTM	1.263***	1.304***	0.911***	-0.424***	-0.448***	-0.294**
	(0.01)	(0.02)	(0.04)	(0.04)	(0.05)	(0.11)
constant	-4.323***	-5.156***	5.377***	-3.733***	8.675***	-7.833***
	(0.31)	(0.33)	(1.56)	(0.29)	(1.51)	(1.43)
industry	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
N	504,628	459,932	44,696	37,425	31,693	5,732
chi2	105,784.7	99,376.9	4,326.8	7,045.9	5,673.4	1,406.2
Structural break test:						
Likelihood Test		102.05 (p=0.00)			0.32 (p=0.85)	
Wald χ^2 Test		106.84 (p=0.00)			0.32 (p=0.57)	
Likelihood Test		142.98 (p=0.00)			8.24 (p=0.32)	

*Notes: Robust standard errors in parentheses. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The devision point of K/L ratio for labor- and capital-intensive sectors is 4. The structural break test is based on an improved test for the discrete choice models. Two likelihood ratio tests examine the equality of the residual variance and the equality of coefficients respectively. The Wald test investigates the equality of the residual variance. "HTM" denotes Hong Kong-, Taiwanese- or Macao-owned firms.*

chapter adopts. More specifically, I first perform a Logit regression for all observations while varying whether or not the variance of residuals is allowed to differ across groups. Then, I test whether the variance of residuals differs across groups using a likelihood ratio and a Wald chi-square test. Finally, using a likelihood ratio test, I examine whether the estimated coefficients are the same for both groups against the alternative that at least one coefficient differs.

The structural break test yields different results for the export-decision and the R&D-decision regressions. For export-decision regressions, both the likelihood ratio test and the Wald chi-square test reject the null hypothesis on the equality of the residual variation. Moreover, the likelihood ratio test rejects the null hypothesis that all coefficients are the same for both labor- and capital-intensive regressions. Hence, it is safe to argue that there is a structural break between labor- and capital-intensive sectors with respect to patterns of the export decision of firms. However, since the likelihood ratio test and the Wald chi-square test do not reject null hypothesis that the variances of the residuals are equal for the R&D-decision regression, there is no evidence of a structural break across sectors for the R&D decision. The likelihood ratio test does not reject the null hypothesis that all coefficients are the same between two regressions of R&D decision. Hence, the following analysis interprete the estimators from the pooled sample for the R&D-decision regression.

As with the OLS results, the coefficients of pooled-sample estimation are quite similar to those of the regression focusing on the labor-intensive sectors. Again, this result most likely occurs because there are much more observations in the labor-intensive regression than in the capital-intensive regression, giving them a larger weight in the pooled sample. In the labor-intensive sectors, the lagged TFP produces a significantly negative effect on the export of firms, which implies that the less productive firms tend to export in those sectors. It is also significantly negative in the pooled regression. In capital-intensive sectors, the lagged TFP exerts a positive influence on the export decision of firms, but it is not significant. On the contrary, lagged TFP shows a significantly positive effect on the decision of firms to invest in R&D, confirming the hypothesis that more productive firms tend to select themselves to conduct R&D across all sectors.

The exporting status yields a significantly positive effect on the R&D decision of firms, meanwhile the presence of R&D investment has a significantly positive effect on the export decision of firms for all regressions. These results jointly suggest that the adoption of either decision improves the probability for firms to adopt the other one, demonstrating a complementarity between the decision to invest in R&D and the decision to export.

Firms in highly capital-intensive sectors are less likely to export, as illustrated from a significantly negative sign of the coefficient of MK/L in capital-intensive regression. According to the proposed theoretical model, this might due to the fact that these sectors have a quite high export productivity cutoff.

Additionally, ownership matters for the decision of firms. Foreign-owned firms show the strongest tendency to export, followed by Hong Kong-, Taiwanese- or Macao-owned firms; however, those firms are less likely to invest in R&D compared to state-owned firms. Non-state-owned indigenous firms are the least likely to invest in R&D.

Higher average wages, which I associate with the presence of more skilled workers, significantly improves the likelihood for firms to export or to invest in R&D. Furthermore, the number of employees is positively correlated with the export decision of firms, but negatively correlated with their R&D decision.

The theoretical model predicts that when firms make their decisions in two steps, exporting may lower the threshold level of productivity required for firms to start R&D investment. On this point, Table 3.5 reports the effect of the exporting status on the decision of firms to start R&D by including an interaction term of lagged TFP and the exporting dummy into a Probit regression. The dependent variable is the decision of firms to start R&D activity for the first time in the dataset.[4] As can be seen from the table, the interaction term has a significantly negative sign, implying that exporting lowers the threshold required for firms to start R&D investment. The lagged TFP has a significantly positive effect on the decision of firms to start R&D, so does the export dummy. The marginal effects, shown in the right column, are estimated at the mean level of the independent variables. According to the outcome, the exporting status lowers the threshold level of productivity for firms to start R&D by 0.004 ($p < 0.1$).

Table 3.5: R&D Starters Conditional on the Exporting Status

	R&D Starter		Marginal Effect	
lagTFP	0.050***	(0.01)	0.006***	(0.00)
export	0.117*	(0.07)	0.016*	(0.01)
exp*lagTFP	-0.029*	(0.02)	-0.004*	(0.00)
K/L	0.020**	(0.01)	0.003**	(0.00)
labor	0.073***	(0.01)	0.009***	(0.00)
avwage	0.107***	(0.02)	0.014***	(0.00)
investment	0.012**	(0.01)	0.002**	(0.00)
non-state-owned	0.082**	(0.04)	0.010**	(0.00)
foreign	0.013	(0.05)	0.002	(0.01)
HTM	0.085	(0.05)	0.012	(0.01)
constant	-2.874***	(0.11)		
industry	yes		yes	
year	yes		yes	
N	34,845		34,845	
chi2	548.18		548.18	

*Notes: Robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "HTM" denotes Hong Kong-, Taiwanese- or Macao-owned firms.*

[4] Two regressions on labor- and capital-intensive sectors are estimated separately. The structural break test does not reject the null hypothesis that the variation of the residual is equal and all coefficients are the same between two regressions.

3.5.3 Multinomial Treatment Effect on Productivity

The multinomial treatment effect model (MTE) is applied to identify the post-decision effect, i.e. whether the interaction of exporting with R&D investment leads to an improvement in productivity. The model utilizes a two-step estimation structure. The decision of firms to export and/or invest in R&D is specified as a mixture multinomial logit model (MMNL) in the selection equation.

$$LD^*_{ij} = \beta \mathbf{x_i} + \kappa \mathbf{z_i} + \beta_j l_{ij} + \eta_{ij}$$
$$Pr(\mathbf{D_i}|\mathbf{x_i}, \mathbf{z_i}, \mathbf{l_i}) = \frac{exp(\beta \mathbf{x_i} + \kappa \mathbf{z_i} + \beta_l l_{ij})}{1+\sum_j exp(\beta \mathbf{x_i} + + \kappa \mathbf{z_i} + \beta_j l_{ij})}$$

where $j = \{00, 10, 01, 11\}$, corresponding to the various categories of decision. The observed decision $D_j = \{(0,0),(1,0),(0,1),(1,1)\}$. LD^* is the latent decision associated with latent factor l_{ij}, which is the unobserved characteristics common to firm i's decision choice and level of productivity, and independent of η_{ij}. The explanatory variable set $\mathbf{x_i}$ includes lagged TFP, the number of employees, the average wages, capital-labor ratio, the ownership dummy, the year dummy and the industry dummy. The instrument variable set $\mathbf{z_i}$ is used to identify the choice of firms, including the median level of capital-labor ratio MK/L, investment and the interaction term of these two variables. The theoretical model suggests that MK/L has a direct effect on firms' decision. Firms in labor-intensive sectors are more likely to export. It is reasonable to assume that a given sector's median K/L ratio has no direct effect on the productivity of firms. Furthermore, I treat Investment as exogenous to the R&D decision of firms. Whereas firms regard the R&D investment as an expenditure and cost in the survey data, its purpose is to achieve profits, which is similar with the traditional function of investment. The idea that investment is not directly correlated with firm productivity derives from Olley and Pakes (1996).

The specification of MMNL relaxes the independence of irrelevant alternatives (IIA) property of multinomial logit model and, therefore, it is more suitable for this analysis.

In the second step, the estimates of productivity are obtained by running a linear regression on corrections, shown in equation (3.11). The unobserved factors l_{ij} enter regressions for both firms decision and productivity. These factors capture the individual-specific factors that induce self-selection into the four exclusive categories through unobservables on the productivity. In oder to identify both regressions simultaneously, the dependent variable, productivity, is assumed to follow a normal distribution, and l_{ij} is assumed to follow the independent standard normal distribution. This specification can be considered as a generalized Heckman two-step estimation. The model is estimated using the maximum likelihood estimation, more specifically, through the simulated function with Halton sequences random draws[5]. Robustness standard errors are used to correct for the heteroscedasticity because they account for uncertainty from finite simulation draws (McFadden and Train, 2000).

$$E(y_i|\mathbf{D_i}, \mathbf{x_i}, \mathbf{l_i}) = \beta\mathbf{x_i} + \sigma_j\beta_j D_{ij} + \sum_j \gamma_j l_{ij} \tag{3.11}$$

According to the supermodularity theory, the complementarity test between exporting and R&D investment is implemented by testing the relationship among the coefficients of four exclusive categories, nonexporters with or without R&D investment, and exporters with or without R&D investment, as shown in equation (3.12). Equation (3.12) implies that adding an additional activity to the existing activity, such as entry to the export market in addition to already conducting R&D, results in a higher incremental performance than engaging in either activity by itself. The validity of the complementarity test requires that the adoption of a decision is uncorrelated with the error term, which is fulfilled by the specification of the MTE estimation.

$$\beta_{11} - \beta_{10} > \beta_{01} - \beta_{00} \tag{3.12}$$

[5] see Deb and Trivedi (2006a) and Deb and Trivedi (2006b) for more technical details.

β_{00} is set to zero, since $D\{X, R\} = (0, 0)$ is dropped due to multicollinearity in the regression.

Table 3.6 reports the multinomial treatment effect result for LP. The base category is non-exporters not pursuing R&D investment. The coefficient of lagged TFP is not significant with respect to firms decision to engage in export only, but it has a significantly positive effect on the decisions of firms to conduct R&D only and to engage in both activities ($EXP * R\&D$). Firms in capital-intensive sectors are less likely to export. the capital-labor ratio (K/L) shows a negative effect on firms' decision to export, but a significantly positive effect for choosing to invest in R&D or to engage in both activities. The foreign-owned firms are more likely to export compared to state-owned firms as well as to participate in both activities.

The likelihood-ratio test (*lrtest*) is applied to examine the exogeneity of firms' decision with respect to the level of productivity. This test essentially reviews the joint hypotheses that the γs are equal to zero using a $\chi^2(3)$ distribution. As can seen from Table 3.6, the *lrtest* rejects the null hypothesis of the exogeneity on the decision-making of firms, hence the first step on the correction of the self-selection is valid. The latent factors, $\gamma export$ and $\gamma EXP * R\&D$, are statistically significant. The results implies that the unobserved characteristics that lead firms to more likely choose export-only relative to the base category (non-exporters not pursuing R&D investment) produce a positive effect on their productivity (0.129), while those unobserved characteristics that cause firms potentially decide to engage in both export and invest in R&D are negatively correlated with firms' productivity (-0.149). $\gamma R\&D$ is not significant.

In the second step, R&D shows a significantly positive effect on LP. The joint decision presents a larger positive effect, while export-only have a negative effect on LP. The complementarity test is a one-side Wald χ^2 test. This test rejects the null hypothesis that $\beta_{11} + \beta_{00} - \beta_{10} - \beta_{01} = 0$, but does not re-

Table 3.6: Multinomial Treatment Effect on Labor Productivity

	Mixture Multinomial Logit Regression			MTE
	Export	R&D	EXP*R&D	Labor Productivity
export-only				-0.123***
				(0.03)
R&D-only				0.050*
				(0.03)
EXP*R&D				0.170***
				(0.02)
lagTFP	0.001	0.236***	0.129***	0.651***
	(0.02)	(0.02)	(0.03)	(0.01)
labor	0.274***	-0.183***	0.351***	-0.433***
	(0.04)	(0.04)	(0.05)	(0.01)
wage	0.296***	0.703***	0.941***	0.295***
	(0.04)	(0.04)	(0.05)	(0.01)
K/L	-0.081***	0.087***	0.158***	0.282***
	(0.02)	(0.02)	(0.02)	(0.00)
MK/L	-0.472*	-0.378**	0.074	
	(0.19)	(0.14)	(0.34)	
investment	-0.170**	-0.045	0.235*	
	(0.06)	(0.06)	(0.09)	
inv*MK/L	0.048***	0.032**	-0.032	
	(0.02)	(0.02)	(0.02)	
non-state-owned	0.747***	-0.182**	0.365***	0.258***
	(0.08)	(0.06)	(0.08)	(0.01)
foreign	2.304***	-0.527***	1.031***	0.305***
	(0.10)	(0.11)	(0.11)	(0.02)
HTM	2.028***	-0.524***	0.659***	0.267***
	(0.10)	(0.11)	(0.12)	(0.02)
constant	-6.504***	-8.124***	-19.233***	-0.053
	(0.75)	(0.60)	(1.33)	(0.04)
industry	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
lnsigma	-0.409*** (0.01)			
γExport	0.129** (0.03)			
γR&D	-0.002 (0.03)			
γEXP*RND	-0.149*** (0.02)			
lrtest	134.32*** (0.00)			
Obs	35,949			
Complementarity test	EXP*R&D>R&D-only +export-only (p=1)			
	EXP*R&D>R&D-only (p=0.999)			

*Notes: Robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Non-exporters not pursuing R&D investment are the base category. 60 Hator sequence-based quasi-random draws per observation. Outcome density is specified as normally distributed. Likelihood test is based on a $\chi^2(3)$ distribution. One-side Wald test is used to examine complementarity.*

Table 3.7: Multinomial Treatment Effect on TFP

	Mixture Multinomial Logit Regression			MTE
	Export	R&D	EXP*R&D	TFP
export-only				-0.151***
				(0.02)
R&D-only				0.049*
				(0.03)
EXP*R&D				0.133***
				(0.02)
lagTFP	0.009	0.241***	0.137***	0.674***
	(0.02)	(0.02)	(0.03)	(0.01)
labor	0.257***	-0.205***	0.296***	-0.259***
	(0.04)	(0.04)	(0.05)	(0.01)
wage	0.307***	0.718***	0.979***	0.265***
	(0.04)	(0.04)	(0.05)	(0.01)
K/L	0.210**	0.306***	1.052***	-0.103***
	(0.07)	(0.07)	(0.12)	(0.01)
$(K/L)^2$	-0.041***	-0.028**	-0.110***	0.008***
	(0.01)	(0.01)	(0.01)	(0.00)
MK/L	-0.489**	-0.406**	-0.076	
	(0.18)	(0.14)	(0.34)	
investment	-0.216***	-0.074	0.144	
	(0.06)	(0.06)	(0.10)	
inv*MK/L	0.061***	0.040*	-0.007	
	(0.02)	(0.02)	(0.03)	
non-state-owned	0.738***	-0.181**	0.383***	0.226***
	(0.08)	(0.06)	(0.08)	(0.01)
foreign	2.313***	-0.519***	1.084***	0.269***
	(0.10)	(0.11)	(0.11)	(0.02)
HTM	2.038***	-0.512***	0.702***	0.236***
	(0.10)	(0.11)	(0.12)	(0.02)
constant	-6.918***	-8.390***	-20.207***	0.781***
	(0.76)	(0.60)	(1.35)	(0.05)
industry	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
lnsigma	-0.432*** (0.02)			
γExport	0.162*** (0.03)			
γR&D	-0.001 (0.02)			
γEXP*RND	-0.130** (0.02)			
lrtest	77.13*** (0.00)			
Obs	35,949			
Complementarity test	EXP*R&D>R&D-only +Export-only (p=1)			
	EXP*R&D>R&D-only (p=0.997)			

*Notes: Robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Non-exporters not pursuing R&D investment are the base category. 60 Hator sequence-based quasi-random draws per observation. Outcome density is specified as normally distributed. Likelihood test is based on a $\chi^2(3)$ distribution. One-side Wald test is used to examine complementarity.*

ject the null hypothesis that $\beta_{11} + \beta_{00} > \beta_{10} + \beta_{01}$ ($p = 1$). Since export-only shows a significantly negative sign on LP, I further compare the coefficients of R&D-only and EXP*R&D. The result implies that doing both activities has a more positive impact on productivity than undertaking R&D investment only $\beta_{11} > \beta_{01}$ ($p = 0.999$). These results jointly confirm the existence of a complementarity between R&D investment and exporting in improving firms' labor productivity.

The MTE result for TFP basically supports the above conclusions of LP regression (Table 3.7), but with a slightly different magnitude. Again, the difference in K/L and $(\mathrm{K/L})^2$ between LP and TFP regressions reflects an intrinsic difference of their conceptual definition. The regression confirms a U-shaped relationship between the capital-labor ratio and TFP.

3.6 Conclusions

The evidence from Chinese manufacturing firms reveals a complementarity between exporting and R&D investment in their impact on firms productivity, and highlights the importance of factor endowments in understanding the exporting behavior of Chinese firms. The structural break test confirms a different pattern for the decision of firms to export for the labor-intensive and capital-intensive sectors in China. In labor-intensive sectors, the less productive firms tend to export, while in capital-intensive sectors, the productivity of firms does not significantly impact the decision to export. The exporting status increases firms' tendency to invest in R&D and vice versa. While the more productive firms select themselves into conducting R&D activities, the exporting status is observed to lower the productivity threshold needed by firms to start R&D investment. Moreover, the interaction of R&D investment and exporting is identified to have a complementary influence on improving the productivity of firms using a multinomial treatment effect model in which self-selection bias from different decisions is disentangled through a mixed multinomial logit regression. These findings hold for both labor productivity and TFP.

This chapter constructs a hybrid model to analyze the decision of firms to export and how it interacts with R&D investment, using Melitz-type firms under a scenario of differing country-specific factor endowments. This modification emphasizes the importance of sector's particularity in understanding the exporting behavior of Chinese firms and the deliberate effort of firms in learning. This extended model derives two different patterns on firms' decision to export and invest in R&D with respect to their productivity for sectors with various factor requirements. In relatively factor-abundant sectors, it is possible that the less productive firms export and the more productive firms invest in R&D to achieve a larger domestic market share, meanwhile most productive firms engage in doing both. In relatively factor-scarce sectors, the more productive firms export and the less productive firms serve the domestic market. Among both exporters and nonexporters, only relatively more productive firms conduct R&D. When firms are assumed to make their decision in two steps, exporting lowers the threshold of productivity in order for firms to invest in R&D in all sectors since the larger market share compensates for the fixed cost of initial R&D investment. Finally, using the supermodularity theory, I prove that R&D investment and exporting are complementary in increasing the profits of firms.

Chapter 4

Foreign Sources of Technology on the Dynamics of Technological Capabilities: Evidence from Firms in Developing Economies

4.1 Introduction

This chapter aims to identify the dynamic patterns of technological capabilities for firms in Eastern European and Central Asian economies and examine the impact of foreign sources of technology on their transitions over time. The concept of "technological capabilities" was originally introduced in the World Bank project "the acquisition of technological capability". Since then, it has been widely used to analyze the successful catching-up of latecomer firms in East Asia, such as Korea and Taiwan, in the 1980s through the1990s (Kim, 1997; Ernst and Kim, 2002; Hobday, 1995) and the failure of their counterparts in Latin American and India (Lall, 1987). Using case studies to analyze either one representative firm or one industry in a certain country, these studies demonstrate that latecomer firms develop their technological capabilities through various sequential stages from the lower level to the advanced level. However, these arguments have not been examined for a large groups of firms.

From the empirical point of view, firms in Eastern European and Central Asian economies are often absent from this area of analysis. Such firms are undergoing the transition to free economic regime and interacting with firms in other European Union economies. Thus, they provide an unique context to study the dynamics of firms in acquiring the technological capabilities, especially how foreign advanced technology influences the development of technology capabilities for latecomer firms.

This chapter contributes to the empirical literature by proposing an econometric model using latent transition analysis to identify the dynamics of technological capabilities for a large group of previously understudied firms. This approach offers a better generalizability of the arguments from previous case studies about the determinants of the transition of firms along sequential stages of technological capabilities, which distinguishes this chapter from previous studies. Consequently, it sheds light on how latecomer firms in developing countries take advantage of foreign sources of technology.

The results can be summarized as follows: (1) The estimated latent transition model identifies three sequential development stages for sampling firms, which supports the arguments from previous case studies about the dynamic patterns of technological capabilities: firms develop the technological capabilities is definable . (2) A comparison of technological capabilities for firms across Eastern European and Central Asian economies shows that Slovenia and Croatia have relatively large share of firms with the advanced level of technological capabilities. Meanwhile, Azerbaijan and Uzbekistan perform the worst owing to the fact that the largest share of firms loads in the basic level. (3) The transition analysis on technological capabilities implies a sticky phenomena: firms tend to remain within their existing stage, therefore their transition towards the higher level of capabilities requires the additional efforts. (4) Different channels of foreign technology yield diverse impacts on the probabilities of firms to change their technological capabilities across various stages. More specifically, the usage of technology licenses helps the transition of firms at all stages towards more advanced levels. While the ratio of imported intermediate inputs plays a more significant role in keeping firms at the intermediate level of technological capabilities and in transitioning of firms towards the advanced level, FDI is observed to have a positive impact on transitioning of firms which only have basic level of technological capabilities. However, the exporting intensity does not show a significant effect on the transition of firms in terms of technological capabilities.

The remainder of the chapter is structured as follows. Section two summarizes the previously conducted related studies. Section three presents the econometric model and its specifications. Section four describes the data source and measurements. Section five provides the empirical results and their corresponding interpretations. The final section summarizes the main research findings of the chapter and discusses possible future studies to elaborate on these findings.

4.2 Literature Review

Despite numerous perspectives among a wide range of studies on the concept, "technological capabilities" essentially refer to firms' ability to master a specific technology, explore it and create new technological knowledge. Kim's (1997) definition, "the ability to make effective use of technological knowledge in efforts to assimilate, use, adapt and change existing technologies", asserts that technological capabilities involve not only the formalized R&D, but also the commercialization of the technology and its customization to the local market. More specifically, three dimensions are acknowledged in analyzing technological capabilities, i.e., production, investment, and innovation capabilities, referring to the ability to maintain and operate the production facilities, the ability to expand capacity and establish new production facilities, and the ability to create new technology and commercialization respectively (Kim, 1997).

4.2.1 Dynamics of technological capabilities

Two lines of research have studied the development of technological capabilities at the firm-level. The first one follows the evolutionary approach in understanding the path of firms to acquisite technological capabilities as a learning process and explore the forces that drive this process (Kim and Nelson, 2000; Bell and Pavitt, 1993).

The second line of research adopts the strategic management and resource-based view to investigate how firms maintain their technological capabilities as the competitive advantages through knowledge management (Teece et al., 1997; Winter, 2003). Technological capabilities act as a bridge to link the resources of firms to the changing business environment. These studies emphasize the role of organizational capabilities in that process.

While the former focuses more on the catching up process and acquiring the minimum essential ability, the latter emphasizes the renewal of technology after accumulating a certain degree of capabilities (Dutrenit, 2004). Both approaches highlight that the developmental process is a moving target and that firms are heterogeneous in building technological capabilities. This reflects that firms have to develop their own strategy to maintain effort in regards to the evolution of technology and the changing environment (Pérez, 2001).

From the resource-based view, the acquisition of technological capabilities by firms can be considered a result of the interaction between internal resources and external resources (Teece et al., 1997). The development of technological capabilities is non-linear, path dependent, and technology specific due to the fact that the evolution of technology *per se* is cumulative and that firms have limited abilities of calculation. Firms can only improve their technological capabilities by searching in zones that enable them to build on their existing technology base. Their success in absorbing the external technology depends on the strategy they develop and effort they put forth, and therefore the outcome is heterogeneous across firms.

Although different studies in the field have utilized diverse terminologies, the accumulating process of technological capabilities by firms has typically been categorized as three dynamic stages ranging from the basic to advanced level. The devision of these levels is based on the performance and the progression of firms in production, investment and innovation. This chapter adopts the taxonomy by Lall (1992) for the three dynamic stages of technological capabilities. Firms with the experience-based level of capabilities perform simple and routine tasks. Next comes search-based capabilities: firms at this stage undertake adaptive and duplicative tasks. They will replicate the production and design from external sources either in order to customize it for the local market or to achieve a more efficient usage through a better understanding of the advanced technology. The role of R&D investment for latecomer firms in this stage is to improve the absorptive capacities, rather than innovating in the knowledge frontier (Cohen and Levinthal, 1989). Firms that succeed in accumulating the search-based capabilities will reach the research-based level. Firms at this advanced level are capable of implementing the innovative and risky tasks. They will set up complete production systems, and design new processes and products, all of which ultimately set the stage for basic or potentially frontier R&D capabilities. Essentially, the acquisition of technological capabilities follows a sequence from simple to complex as with the nature of learning process.

The transition of firms in terms of technological capabilities corresponds to corresponds to the heavy investment in purchasing machineries, upgrading production lines, or training workers at the initial stage of development. This process is described as progressing from capital accumulation to technological assimilation by Nelson and Pack (1999) in their explanation of the Asian miracles. When aggregating at the industry and country levels, the important linkage of different agents and actors as well as the national policy (Kim, 1997; Lall, 1998; Bell and Pavitt, 1993), such as trade or technology policy, are what leads to the discussion of national innovation system (Freeman, 1974).

4.2.2 Technological capabilities and foreign sources of technology

The successful catching-up of firms in East Asian economies highlights foreign advanced technology as one of the most important sources for the accumulation of technological capabilities from the experience-based to the research-based level. The transitions of firms to more advanced level of capabilities is a process of "reverse engineering" (Kim, 1997). Different channels of foreign technology have been observed to contribute to the transition of firms in terms of technological capabilities. These channels can be: (1) the transmission of ideas traded independence of goods, such as patent licensing and FDI, or (2) trading in intermediate and capital goods that embody technology. Each option offers unique advantages and disadvantages and plays a different role in firm learning at various stages.

It is argued that direct sources of foreign technology are more important for the early phase of accumulation. Imported intermediate inputs and technology licenses embody the readily-use technology from the foreign origins. Imported intermediate inputs improve the production process of firms directly. Investment in machinery and equipment is observed to have a strong impact on total factor productivity and the growth of importing firms (De Long and Summers, 1991; Almeida and Fernandes, 2008; Acharya and Keller, 2009). Patent licenses facilitate the introduction of new technology or products which are already established or readily available in firms from developed economies. However, successful implementation of licensed patents requires both tacit knowledge and skilled workers; hence it stimulates the process of learning. FDI may bring a new production set and new technology for firms that receive direct investment, on the one hand. On the other hand, parent firms abroad will try to protect their advanced technology from diffusing to the local firms in order to prevent their monopoly positions from eroding (Saggi, 2002). Therefore, FDI is more likely to facilitate technological capabilities improvements for firms at the early stage. Kim (1997) argues that technology licenses and turnkey were especially important for the initial accumulating process of catching-up by Samsung and Hyundai. Through original equipment manufacturing (OEM) and in-plant training, firms develop their own strategy to absorb and implement the advanced foreign technology. However, once it is assimilated by firms, the foreign technology itself is not as important as in the initial stage. Firms start to compete on the international market after they develop their own capabilities.

Exporting contributes to the development of technological capabilities in an indirect way by allowing local reverse engineering and access to new machineries and equipments. Many latecomer economies adopt the export-oriented strategy during their development, such as Korea, Taiwan and Indonesia (Ernst et al., 1998). Firms in Korea have shown better performance in assimilating foreign technology through organized efforts toward R&D and in-plant training. Exporters have been observed to generate higher level of productivity in Slovenia after foreign sales are initiated (De Loecker, 2007) as well as in certain industries in Taiwan (Aw et al., 2001). Still, the incidental learning through exporting does not occur for firms in most economies. Exporters need additional efforts and basic capabilities to assimilate the indirect knowledge; consequently, exporting is supposed to encourage the transition of firms towards an advanced level.

The path of technological learning, moving through identifiable stages towards the acquisition of technological capabilities, is observed for representative firms in automobile, electronics, chemical, and machinery industries in Korea, Taiwan and Japan from early 1960s through the 1990s (Kim, 1997; Kim and Nelson, 2000; Dahlman et al., 1987; Lee and Lim, 2001).

Those analyses provide guidelines for both firm-level strategies and government policies. However, the theory of the accumulation of technological capabilities has normally been analyzed utilizing case studies, focusing on large firms in either one single industry or country (Fagerberg et al., 2009). Few studies examine the development of technological capabilities throughout the experience-based to the research-based level for a large number of firms. The difficulty lies in lacking of an appropriate indicator or approach to capture technological capabilities owing to the fact that the concept of "capability" incorporates multi-dimensional factors in production, investment, and innovation, all of which must be combined in such a way to provide a comprehensive, yet measurable structure in order to implement the econometric analysis. The existing empirical studies adopt either a single indicator to measure technological capabilities, such as R&D investment or on-job training (Aw and Batra, 1998), the number of patents (Motohashi, 2008), or an aggregate index calculated through an arbitrary combination (e.g., average) of different determinants (Archibugi and Coco, 2004). The latter is also applied to evaluate the technological capabilities at the country level by UNCAD. None of approaches are capable of capturing the comprehensive implicitness of technological capabilities, nor of identifying the transitions of firms.

This chapter proposes a latent transition model to estimate simultaneously whether firms belong to the same category of technological capabilities as well as the probability of firms transitioning among latent states over time. The result is achieved without assuming any pre-determined cluster structures. With this approach, it is possible to generalize the arguments from case studies about the determinants of the transition of firms along sequential stages of technological capabilities. The determinants of such a transition are estimated using a combination of latent transition analysis and multinomial logistic regression to analyze different channels of foreign technology, i.e., FDI, technology licenses, imported intermediate inputs and the exporting intensity.

4.3 Econometric Model and Estimation Strategy

The latent transition analysis (hereafter "LTA"), otherwise known as "hidden Markov model" in the field of engineering, is applied to estimate a firm's class membership with respect to their technological capabilities and to identify the dynamic stage of its development.[1] This model extends the "latent class model" to repeated measurements (Visser et al., 2009).

4.3.1 Assumption and notations

A finite state space of technological capabilities $S = S_1, \ldots, S_n$, is not directly observable to analysts, but attached with three manifest dimensions of production performance, investment capability and innovation outcome.

Whether firms fall into a certain identifiable latent state in terms of their technological capabilities is based on the measurement model on the observable k factors $\mathbf{O} = (O_1, \ldots, O_k)$. Each state has a probability distribution over the possible observable items. The probability distribution of observation variables in state i is denoted by B_i for $i = 1, 2, \ldots, n$. Local independence is assumed, i.e., the observed variables are independent conditional on the underlying state. This is a common assumption in latent variable models.

The transition dynamics of technological capabilities by firms is assumed to follow a first-order Markov process with the unobserved states, formalized as equation 4.1.

$$p(S_t|S_1, S_2, \ldots, S_{t-1}) = p(S_t|S_{t-1}) \tag{4.1}$$

This is in line with the idea that the development of technological capabilities is path dependent as argued by the studies with evolutionary approach (Nelson and Winter, 1982).

[1] It is called "latent Markov model" in the field of sociology and psychology. This model has been applied to analyze the learning process, speech recognition and change of human behavior.

The transition model A provides transition probabilities $a_{ij} = P[S_{t+1} = S_j | S_t = S_i]$ for $1 \leqslant i, j \leqslant n$. The transition process is ergodic, that is, there are no absorbing states. Each level of technological capabilities can be reached from any other level. Because the development of technological capabilities for firms is a moving target, if firms with higher level of technological capabilities withdraw their efforts in acquiring technology, they will probably fall behind and switch to a lower level of technological capabilities.

The transition probabilities are influenced by foreign sources of technology $\mathbf{F_t} = (F_{t1}, F_{t2}, \ldots, F_{tm})$.

4.3.2 Econometric model

Based on these assumption and notations, LTA with three states is illustrated in Figure 4.1.

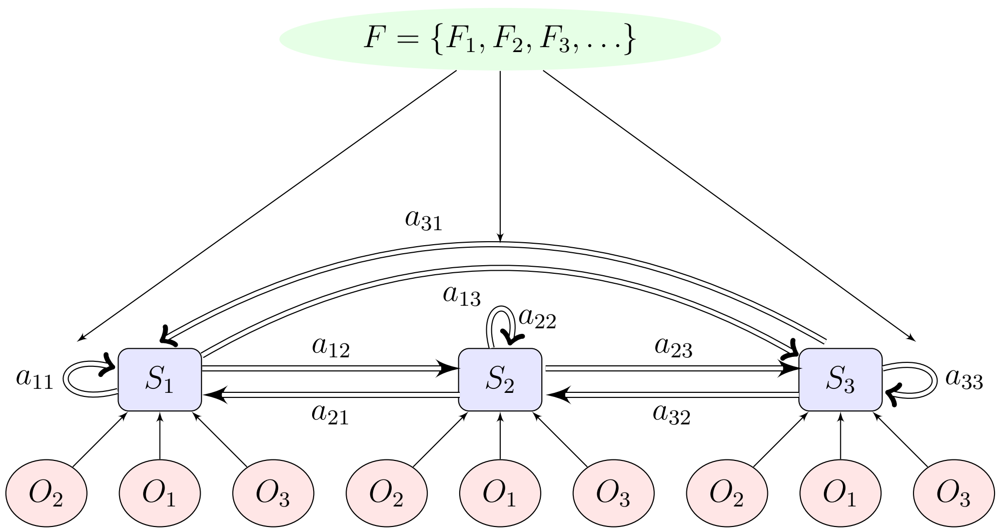


Figure 4.1: Latent Transition Model with 3 States

A LTA can be used to generate an observation sequence of technological capabilities, given the number of states n, the distribution of observable factors B and the initial state distribution π. The probability of a firm's certain realization pattern $\mathbf{O_i} = (o_{i1}, \ldots, o_{ik})$ at time t can be written as

$$P[O_T = o_i|\lambda] = \sum_{S=1}^{n} \pi_1 B_{S_1=i}(O_1) \prod_{t=1}^{T} a_{S_{t-1}=i,S_t=j} B_{S_t=j}(O_t) \tag{4.2}$$

where λ is the parameter vector containing parameters to model π, A, and B. The sum runs over all possible sequences $S_1, \ldots, S_T$ of the latent or hidden state sequence, and the product runs from $t = 2$ to T.

Under the assumption of local independence, the distribution function is $B_i(O_t) = \prod_{j=1\ldots m} B_i(O_j)$. The probability that a firm has class membership S is achieved by maximizing the conditional probability in an iterative procedure.

$$s_t = \arg\max_{1\leqslant i\leqslant n}\{\gamma_t(i)\} = \arg\max_{1\leqslant i\leqslant n}\{p[s_t = S_i|\mathbf{O}, \lambda]\} \tag{4.3}$$

with $\sum_{i=1}^{n} \gamma_t(i) = 1$.

Heterogeneity can be controlled by specifying separate distribution functions for each measurement period. This chapter adopts a latent transition logistic regression model proposed by Chung et al. (2007) to examine the stage-sequential pattern of the transitions of firms over periods as the alternative control of heterogeneity. The specification of a multinomial logistic regression for the transition probabilities is used to model the probability of being in a current stage conditionally on both the prior stage and covariates of foreign sources of technology. Parameters of distributions are the function of time-varying variables $\mathbf{F_t}$, that is, $a_{ij} = P(S_t = j|S_{t-1} = i, F_t)$. The transition probabilities from state i are modeled as a baseline category logit model:

$$log(a_{ij}/a_{i1}) = \alpha_j + \beta_\mathbf{j}\mathbf{F_t}, j = 2, \ldots, n \tag{4.4}$$

Parameters of LTA are estimated by optimizing the log-likelihood, with EM (expectation maximization) algorithm or gradients of the parameters for log-likelihood. The latter algorithm has advantages to deal with box constraints on parameters and general linear constraints between parameters (Visser and Speekenbrink, 2010). Akaike and Bayesian information criteria are used to decide the goodness of fit among models in order to determine the number of unobserved states. Lower AICs and BICs normally indicate the better-fitting models. This criteria are normally valid and perform well for LTA models according to Paliouras (2007)

Compared to its alternative – a two-step estimation of the conventional cluster and a multinomial logistic regression, the LTA model is superior in the following three aspects. First, this approach is capable of estimating the state and its transition simultaneously by maximizing the possible state sequence. In this sense, LTA captures firm heterogeneity and the dynamic mechanism to some degree. Second, the measurement model does not specify any pre-determined cluster structure or linear combination of the variables. Third, LTA can deal with discrete variables more efficiently and such variables more often occur in the firm-level survey data in the field of economics.

4.4 Data

The data comes from the Business Environment and Enterprise Performance Survey (BEEP), collected jointly by the European Bank for Reconstruction and Development and the World Bank. The survey covers 23,570 firms with at least five full-time employees from 27 Eastern European and Central Asian economies between 2002 and 2009. It forms an unbalanced panel structure with intervals of three to four years. This data provides detailed information about characteristics, economic performance, innovation, investment environment, and degree of competition. The samples are designed to have a representative picture of industries for each economy. These firms are from both manufacturing and service sectors, identified at the ISIC 4-digit level.

4.4.1 Measurement and specification

The measurement model includes seven variables that are categorized in three dimensions of production, investment and innovation in order for estimating the sequential stages of technological capabilities. Four channels are used to identify the influence of foreign sources of technology on the transition probabilities. Table 4.1 describes the measurements for these variables and respective specifications.

4.4.2 Descriptive statistics

Observations with either missing values for variable SKL or in year 2007 are excluded from the following analysis. This is due to the estimation of this model is highly sensitive to the setup of the missing value in continuous variables and small proportion of surveyed firm in 2007.[2] This results in 18,641 observations with three periods in 2002, 2005 and 2009.

Table C.1 in Appendix reports the descriptive statistics for the four continuous variables and the categorical distributions for the six discrete variables. All categorical variables are binary, except for the internationally-recognized quality certificate (ISO) a multinomial variable. The correlation coefficients between seven variables used in the measurement model are shown in Table 4.2. Although most of the correlation coefficients are highly significant except the correlation between job training and production capacity, only production innovation PDI and process innovation PCI are highly correlated (0.46).

[2]Only 1,952 firms were surveyed in 2007, among which, 1,072 firms are from Bulgaria.

Table 4.1: Variables and Measurements

Factor	Dimension	Variable	Measurement	Type	Distribution*
O	Production capabilities	ISO	Internationally recognized quality certification	Categorical	Multinomial†
		SKL	The ratio of skilled workers to all employees	Continuous	Gaussian
		PRC	Production capacity	Continuous	Gaussian
	Investment decision	R&D	R&D investment	Categorical	Binary
		JBT	The presence of on-job training	Categorical	Binary
	Innovation outcome	PDI	The presence of new product in sales	Categorical	Binary
		PCI	Upgrading the production line in the past three years	Categorical	Binary
F	Direct	TCL	The usage of foreign technology licenses	Categorical	-
		FDI	The percentage of capital from private foreign organizations or individuals to overall capital	Continuous	-
		IMP	The proportion of all materials inputs or supplies purchased from foreign origins	Continuous	-
	Indirect	EXP	The ratio of direct export to annual sales	Continuous	-

*Notes: *The distribution used in the measurement model. † Except for "yes" or "no", ISO includes a category "in process" which is 1 if a firm has applied for certification but not be granted yet.*

Table 4.2: Correlation Table

	SKL	PRC	ISO	R&D	JBT	PDI	PCI
SKL	1						
PRC	0.02***	1					
ISO	0.03***	-0.02***	1				
R&D	0.04***	-0.07***	0.17***	1			
JBT	0.09***	0.01	0.19***	0.12***	1		
PDI	0.01*	-0.04***	0.2***	0.15***	0.16***	1	
PCI	0.07***	-0.02***	0.18***	0.16***	0.18***	0.46***	1

*Notes: Significance level: * $p<0.05$, ** $p<0.01$,*** $p<0.001$*

4.5 Results

The LTA model is applied to the BEEP data to differentiate the experience-based, search-based and research-based levels of technological capabilities for sampling firms as well as their transitions along various level of capabilities over time.

4.5.1 Model selection and stage segment

In order to achieve the optimal number of stages along the development of technological capabilities and identify the sequential patterns, LTA models with 2-, 3- or 4-state are fitted to the data[3]. The continuous variable SKL and PRC are specified as a Gaussian distribution in the measurement model, with ISO, $R\&D$, JBT, PDI and PCI multinomial indicators. Missing values in those multinomial variables are set to one category. Models are estimated with or without production capacity. Variables used to measure latent states are by nature unverifiable. This study determines these variables and the optimal model based on both goodness-of-fit measurement and the implicitness of the concept suggested by previous case studies. The goodness-of-fit measurements for models in question are reported and com-

[3] "State" and "stage" are interchangable in the following description.

pared in Table 4.3, with a 'pc' denoting a model that includes the variable of production capacity.

Table 4.3: Goodness-of-fit Measures for Model Selection

Models	logl	AIC	BIC	nfree	N
2	-67,062.7	134,183.3	134,410.3	29	18,513
3	-66,649.9	133,393.7	133,761.5	47	18,513
4	-66,639.6	133,413.2	133,937.5	67	18,513
2pc	-152,101.2	304,268.3	304,526.6	33	18,513
3pc	75,300.8†	-150,495.6	-150,080.8	53	18,513
4pc	76,418.2†	-152,686.5	-152,099.5	75	18,513

Notes: '-pc' denotes a model that includes the variable of production capacity. † Positive log-likelihood occurs when the density function of continuous variable PRC is larger than 1. The initial parameters of state distribution are set to (0.6, 0.4), (0.6, 0.3, 0.1), and (0.6, 0.3, 0.05, 0.05) for 2-, 3-, 4-state respectively.

As can be seen from Table 4.3, the three-state specification has best goodness-of-fit statistics among LTA estimations with and without production capacity respectively. Each of 3-stage specification produces the lower AICs and BICs (algebra value) compared to either 2- or 4-state models within each group. This indicates a three-stage pattern of technological capabilities among sampling firms. Incorporating the variable of production capacity into LTA does not improve the goodness-of-fit measure. Consequently, PRC is excluded from the following analysis.[4] The three-state LTA model without production capacity is preferred to analyze the transition probabilities. This result provides the tentative support for the 3-stage dynamic framework proposed by previous case studies. More details on the characteristics of each state or stage along the development are reported in Table 4.4.

Parameters in each row of Table 4.4 describe the average performance of

[4] It is dropped also because of the vague interpretation. It is not straightforward to argue the higher the production capacity is, the better technological capabilities is, or the other way around.

Table 4.4: Stage Segment

	Production				Investment				Innovation			
	SKL*	ISO			R&D		JBT		PDI		PCI	
	Gaussian	No	IP[†]	Yes	No	Yes	No	Yes	No	Yes	No	Yes
S_1	0.47 (0.32)	0.93	0.00	0.06	0.40	0.07	0.76	0.24	0.90	0.10	0.83	0.17
S_2	0.51 (0.29)	0.89	0.00	0.11	0.44	0.15	0.66	0.34	0.35	0.65	0.07	0.93
S_3	0.54 (0.25)	0.48	0.02	0.50	0.26	0.50	0.23	0.77	0.25	0.75	0.12	0.88
N	18,513											
AIC	133,393.7											
BIC	133,761.5											

*Notes: *Standard deviation in the parentheses. [†]'IP' denotes "in process". Probabilities at zero values of the covariates.*

firms at each stage in terms of six variables used in 3-state LTA estimation. These variables measure the technological capabilities as the gatherings of performance in production, investment and innovation. Firms at stage 3 show the superior performance to the other two groups. They have the highest ratio of skilled workers (0.54) and are most likely to have an internationally recognized quality certifications (0.50), to invest in R&D activities (0.50) and job training (0.77), and to undertake product innovation (0.75), but with the intermediate level of likelihood to engage in the process innovation (0.88). Meanwhile, firms in stage 1 display the worst performance. Therefore, it is arguable that the sequential stages along the development of technological capabilities is from S_1 with the basic level, then moves to S_2, and further to S_3 with relatively high level. Accordingly, S_1, S_2 and S_3 are tagged as the experience-based, search-based and research-based stage of technological capabilities respectively. Firms at the search-based stage have the highest tendency to conduct process innovation. This reflects a process of reverse engineering. In other words, firms tend to upgrade the production line before they engage in frontier R&D activity and build their own technological capabilities.

The initial state probabilities for three stages from basic to advanced level are 0.48, 0.33 and 0.19 respectively. The estimated transition probabilities matrix is shown in Table 4.5. The diagonal elements of this matrix have the largest value compared to other elements within each column or row. This can be interpreted as a certain level of sticky phenomena – firms have the highest probability of remaining in their existing stage. The probabilities of remaining in the same previous stage, a_{11}, a_{22}, and a_{33} are 0.70, 0.61 and 0.89 respectively. However, as long as firms develop the research-based level of technological capabilities, they tend to keep their advantages in the future owing to the fact that firms at the research-based level have the largest probability to remain in the same stage for the next period. It is worth noting that firms in the search-based level have a probability of 0.27 to lose their advantages and regress to the experience-based level.

Table 4.5: Transition Probabilities Matrix

	Experience-based	Search-based	Research-based
Experience-based	0.70	0.22	0.09
Search-based	0.27	0.61	0.12
Research-based	0.10	0.00	0.89

Notes: Probabilities at zero values of the covariates.

4.5.2 Technological capabilities across economies

According to the estimated 3-state LTA model, each observation can be allocated to its most probable stage membership in terms of technological capabilities for each period. This membership is calculated based on the posterior estimation of the state sequence using the Viterbi algorithm (See Rabiner (1989) for more technical details.). Consequently, 8,186 observations load in stage 1 – experience-based level, with 7,177 and 3,150 in stage 2 and 3 respectively.

Table 4.6 reports the number of firms at various stages across economies

Table 4.6: Comparison of Technological Capabilities across Economies

	2002			2005			2009			Share of stages		
Economy	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3
Albania	105	40	21	112	61	30	7	8	5	0.58	0.28	0.14
Armenia	107	45	18	163	158	30	24	54	34	0.46	0.41	0.13
Azerbaijan	121	33	12	264	69	16	46	56	18	0.68	0.25	0.07
Belarus	111	85	53	145	134	40	5	52	22	0.40	0.42	0.18
Bosnia	84	61	26	78	87	27	11	42	69	0.36	0.39	0.25
Bulgaria	131	82	34	192	79	28	30	32	29	0.55	0.30	0.14
Croatia	60	70	47	55	122	55	4	10	20	0.27	0.46	0.28
Czech Rep.	156	70	37	183	58	40	12	15	53	0.56	0.23	0.21
Estonia	81	50	36	103	80	33	15	33	39	0.42	0.35	0.23
Macedonia	117	40	6	118	56	26	23	56	35	0.54	0.32	0.14
Georgia	99	58	16	122	55	18	26	68	18	0.51	0.38	0.11
Hungary	167	32	39	377	138	93	25	53	23	0.60	0.24	0.16
Kazakhstan	155	59	33	354	190	41	47	84	39	0.55	0.33	0.11
Kyrgyz	88	57	24	95	78	29	29	49	14	0.46	0.40	0.14
Latvia	83	51	34	98	74	32	4	47	35	0.40	0.38	0.22
Lithuania	111	39	48	105	64	33	5	56	32	0.45	0.32	0.23
Moldova	88	62	23	159	160	27	32	51	27	0.44	0.43	0.12
Montenegro	9	8	0	10	7	0	12	13	8	0.46	0.42	0.12
Poland	252	139	101	519	309	145	39	44	57	0.50	0.31	0.19
Romania	114	98	40	307	219	72	69	51	58	0.48	0.36	0.17
Russia	285	144	70	334	208	53	63	299	216	0.41	0.39	0.20
Serbia	122	81	25	118	119	40	24	43	65	0.41	0.38	0.20
Slovakia	56	62	49	80	104	31	17	32	34	0.33	0.43	0.25
Slovenia	108	23	57	148	22	53	9	30	57	0.52	0.15	0.33
Tajikistan	94	57	23	109	71	20	19	79	14	0.46	0.43	0.12
Ukraine	179	153	69	242	292	57	95	271	96	0.35	0.49	0.15
Uzbekistan	165	62	32	252	42	6	70	42	9	0.72	0.21	0.07

Notes: The result is the posterior estimation of the state sequence based on the estimated 3-state LTA model. S_1*,* S_2 *and* S_3 *correspond to the experience-based, search-based and research-based level of technological capabilities respectively.*

for the three survey periods. The share of overall observations distributed to three stages for each economy can be found in the last block of column. The result is further illustrated in Figure 4.2. The comparison suggests that Slovenia has highest share (0.33) of firms in the research-based level, followed by Croatia (0.28), Slovakia (0.25) and Bosnia (0.25), meanwhile most of the firms in Eastern European and Central Asian economies are still in the lower level of development. A large proportion of observations in Uzbekistan (0.72), Azerbaijan (0.68), Hungary (0.60) and Albania (0.58) loads in the experience-based level. Among these economies, Ukraine (0.49), Croatia (0.46), Moldova (0.43) and Tajikistan (0.43) have the highest ratio of observations at the search-based level. This argument with respect to the macro-level comparison is based on the performance of firms which are covered in the BEEP. To which degree this can be generalized to the whole economies depends on the representativeness of firms sampled.[5]

4.5.3 Channels of foreign technology on the transition probabilities

The impacts of foreign sources of technology on the transition probabilities are explored by including four variables – the usage of technology licenses (TCL), the proportion of imported intermediate inputs (IMP), the ratio of direct export to total sales (EXP) and the share of firms owned by foreign organizations (FDI) – in a multinomial logistic model as specified in equation (4.4).

Observations that incorporate missing values in their variables IMP, EXP and FDI are dropped from the analysis in order to exclude the influence of the setup of missing values on the estimation. This results in a subsample of 17,396 observations, with 93 firms surveyed in all three periods

[5] It would be too ambitious to argue this result reflects the performance of the whole economies. This part of analysis serves as illustrating the application of LTA model by showing a snapshot of the aggregate performance.

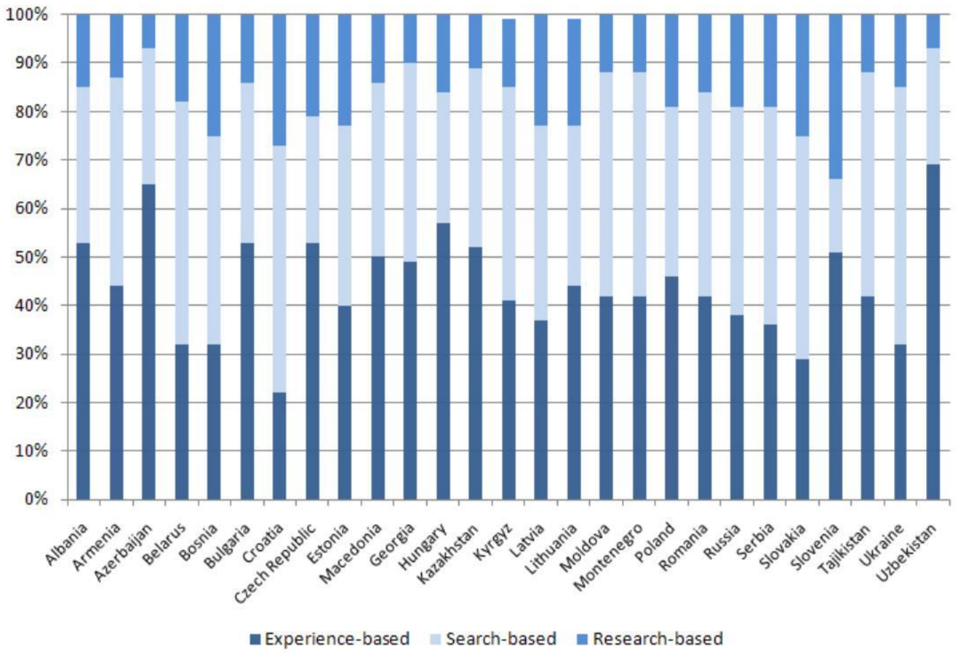


Figure 4.2: Comparison of Technological Capabilities across Economies

and 1,622 firms two periods. The 3-state LTA with and without covariates of the channels of foreign technology on the transition probabilities are fitted to the generated subsample. Table 4.7 compares the goodness-of-fit statistics for both models, with '-f' indicating the model that includes the variables of foreign sources of technology. The log likelihood ratio test (llr) indicates that the inclusion of foreign sources of technology improves the goodness-of-fit significantly, with log likelihood ratio 134.2 ($p = 0$). Furthermore, the model with covariates produces the lower AIC and BIC values. Consequently, it is arguable that foreign sources of technology have significantly impact on the transition of firms along various stages of technological capabilities.

Table 4.8 reports the influence of foreign technology on the transition dynamics for firms at various levels of technological capabilities. The baseline category is stage 1 for all levels of firms, which leads to the zero values for the first column of every stage block, with log-odds scale for other columns.

Table 4.7: Goodness-of-fit Measures for Transition Probabilities with Covariates

Models	logl	AIC	BIC	nfree	llr	df(p)	N
3	-62,380.1	124,854.2	125,219.1	47			17,396
3f	-62,245.9	124,634.8	125,186.1	71	134.2	24(0)	17,396

Notes: '-f' denotes a model with covariates of foreign sources of technology. The initial parameters for state distribution are set to (0.6, 0.3, 0.1) for both models.

Table 4.8: Transition Probabilities with Covariates

		S_1			S_2			S_3	
Var	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3
TCL	0.000	1.034	1.801	0.000	0.178	1.329	0.000	-0.436	0.625
FDI	0.000	0.016	0.010	0.000	-0.005	0.004	0.000	-0.056	-0.007
IMP	0.000	0.002	0.013	0.000	0.006	0.002	0.000	0.260	0.258
EXP	0.000	-0.000	0.013	0.000	-0.002	0.003	0.000	-0.180	0.196
constant	0.000	-1.999	-4.332	0.000	0.082	-2.312	0.000	0.434	0.126
$p(trn)$	0.870	0.118	0.011	0.458	0.497	0.045	0.271	0.420	0.308
N	17,396								
AIC	124,634.8								
BIC	125,186.1								

Notes: $p(trn)$ is transition probabilities. Probabilities at zero values of the covariates.

The result reveals quite diverse impacts for different channels of foreign technology on the transition probabilities for firms at various level of capabilities. The usage of technology licenses shows the largest effect on the transition probabilities, especially on the transition of firms from stage 1 to stage 2 and 3. TCL increases the log-ratio of two probabilities $a12/a11$ and $a13/a11$ by 1.034 and 1.801 respectively. Meanwhile, it presents a manifest impact on the transition of firms from stage 2 to stage 3 rather than switching to stage 1 (1.329).

While FDI shows a positive effect on the transition probabilities from stage 1 to stage 2 and 3, it does not show effects for firms at more advanced stage.[6]

The ratio of imported intermediate inputs yields a relatively large effect on remaining the advanced technological capabilities rather than falling down to the experience-based level (0.258). The export intensity shows the least impact on the transition probabilities, which can be seen from their lowest coefficients and even negative signs, although its effect is more obvious on keeping firms in the reseach-based stage (0.196).

In order to get comparable results, the marginal effects of each variable on the transition probabilities are estimated at the median point of other three variables. A smoothing curve between possible values for each channel of foreign technology and the predicted transition probabilities is plotted in Figure 4.3. 'txy' in the legend denotes the transition of firms from stage 'x' to stage 'y'. The transition dynamics from the lower stages to the higher stages or remaining in the same higher stage is the interest of this chapter. This corresponds to five elements in the upper triangular of the transition matrix (excluding a_{11}). Therefore, five lines are plotted on each graph.

The usage of technology licenses improves the transition probabilities for firms from stage 1 or 2 to stage 3 to largest degree since line t13 and t23 in figure 4.3a display the steepest trend on the transition from point 2 (no technology license) to point 3 (the usage of technology licenses). It also has a positive effect on remaining the advanced level of the technological capabilities (line t33 in figure 4.3a). The ratio of imported intermediate inputs is more relevant for the transition of firms from stage 1 to stage 3 (line t13 in figure 4.3c) and remaining at stage 3 (line t33 in figure 4.3c). FDI plays a more important role in the transition of firms from stage 1 to stage 2 (line t12 in figure 4.3d) and from stage 2 to stage 3 (line t23 in figure 4.3d). The exporting intensity does not show a positive effect on the preferred transition of technological capabilities. It only shows the limited

[6] The measurement of FDI in this chapter is a rarely time-variant variable. It might be more appropriate to specify it as the covariate on the prior probability of a firm's initial state.

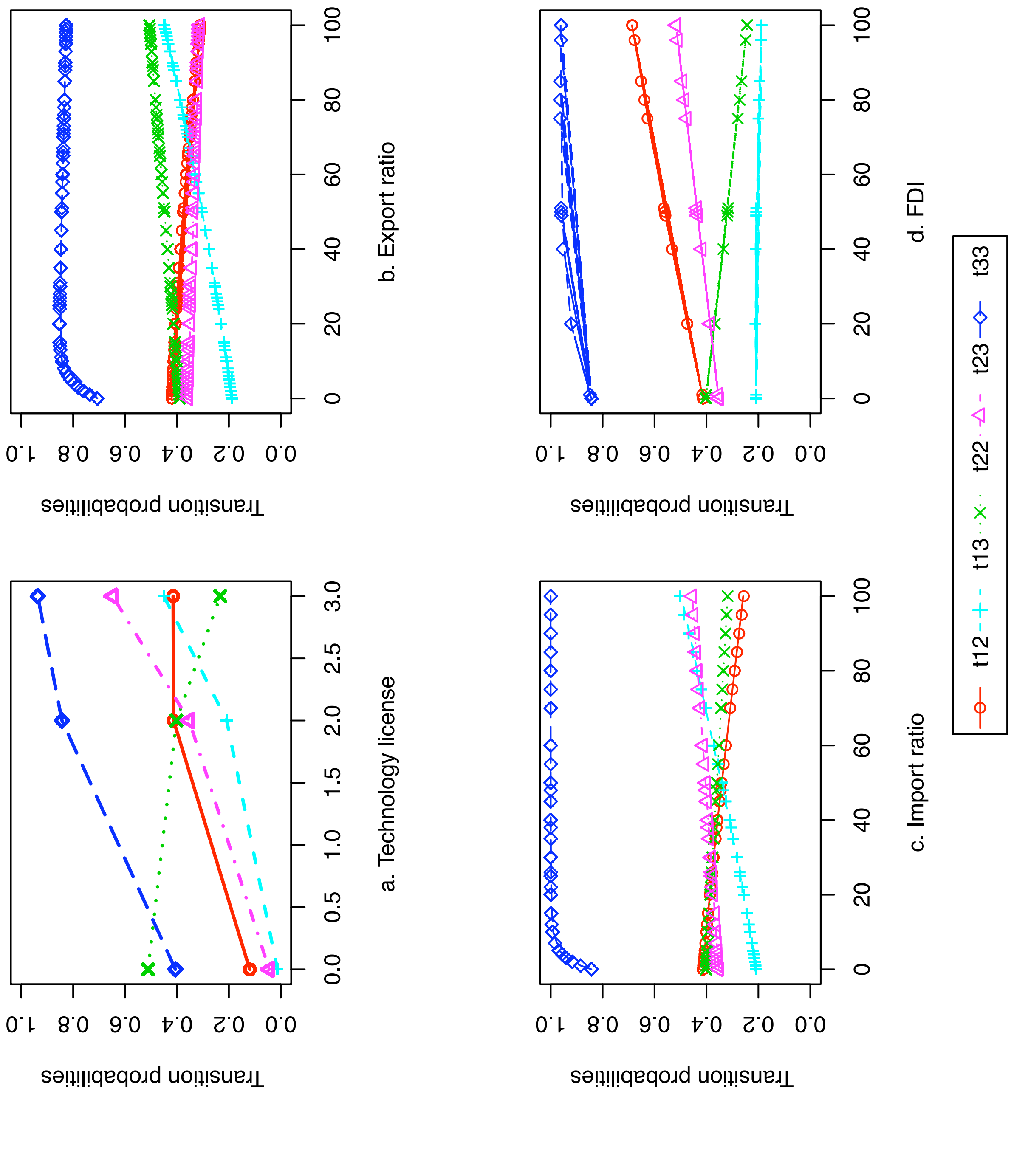


Figure 4.3: Foreign Sources of Technology on the Transition Dynamics

Notes: 'txy' in the legend denotes the transition from stage x to stage y.

effect on the transition from stage 1 to stage 3 (line t13 in figure 4.3b).

Consequently, it is arguable that the direct sources of foreign technology are more important for the transition of firms in Eastern European and Central Asian economies. The usage of technology licenses plays a important role for the transition of technological capabilities for firms at all stages. Among firms with basic technological capabilities, FDI has a positive impact on transitioning. Moreover, imported intermediate inputs help remaining firms at the advanced level.

4.5.4 Robustness check

First, the correlated relationship among variables used in the measurement model are estimated within each stage group of firms in order to examine whether the assumption of local independence is fulfilled. As shown in Table 4.9, there are no significantly high correlations among variables within each subgroup. Although most correlation coefficients are statistically significant, the highest level of correlation occurs between $R\&D$ and ISO in stage 3 only with the value of -0.24. This result can be considered to support the assumption of local independence.

Second, the observations that do not include missing values for continuous variables are extracted from the sample and pooled together. A two-step estimation of latent class model and cross-sectional multinomial logistic regression is used to fit this pooled data. The 3-state latent class estimation generates 7,238, 6,780 and 3,378 observations at state 1, 2 and 3 respectively. The result is quite similar with what LTA produces, of 7,377, 6,954 and 3,065 observations.[7] Table 4.10 reports the cross-sectional estimation of the multinomial logistic regression.

Similar as before, the baseline category is state 1 for each level of ca-

[7]The parameters of state segment are also similar. They are available at requests.

Table 4.9: Correlation Coefficients in Each Stage

	SKL	PRC	ISO	R&D	JBT	PDI	PCI
				S_1, N=8,852			
SKL	1						
PRC	0.02**	1					
ISO	0.03***	-0.03***	1				
R&D	0.02	-0.05***	0.06***	1			
JBT	0.11***	0	0.08***	0.07***	1		
PDI	-0.01	-0.02**	0.01	-0.02**	0	1	
PCI	-0.03***	0.01	-0.09***	-0.2***	-0.15***	-0.14***	1
				S_2, N=6,487			
SKL	1						
PRC	0.03**	1					
ISO	-0.04***	-0.02	1				
R&D	0.02*	-0.08***	-0.04***	1			
JBT	0.04***	0.05***	-0.22***	-0.23***	1		
PDI	-0.1***	-0.02*	0	-0.13***	-0.11***	1	
PCI	0.01	0	0.01	-0.06***	-0.01	-0.05***	1
				S_3, N=3,174			
SKL	1						
PRC	0.02	1					
ISO	-0.01	0.05***	1				
R&D	-0.01	-0.06***	-0.17***	1			
JBT	-0.01	0.1***	-0.06***	-0.05***	1		
PDI	-0.03*	0.03*	0.14***	0.13***	0.1***	1	
PCI	0.03*	0.07***	0.15***	0.09***	0.14***	0.31***	1

*Notes: Significance level: * p<0.1, ** p<0.05,*** p<0.01.*

pabilities. This estimation basically supports the 3-state LTA estimation, except for a significantly negative effect of export on remaining the advanced level of capabilities in state 3 and the larger magnitude of the coefficients on TCL and IMP in state 3. The usage of technology licenses shows a significantly positive effect on the transition probabilities towards to higher levels for firms at all stages. FDI only has a significant positive effect on transitioning to the higher level for firms at state 1. Moreover, the ratio of imported intermediate inputs produces the positive effect on the transition of firms at stage 2 and from stage 1 to stage 3. However, the export intensity

Table 4.10: Cross-sectional Multinomial Regression on Transitions

	S_1		S_2		S_3
Var	S_2	S_3	S_2	S_3	S_3
TCL	0.678***	1.099***	0.164*	0.779***	0.573***
	(-7.13)	(-8.86)	(-6.9)	(-1.73)	(-0.76)
FDI	0.009***	0.011***	-0.004	0.002	0.004
	(-2.67)	(-2.63)	(-0.49)	(-1.27)	(-0.21)
IMP	0.001	0.009***	0.005*	0.006**	0.007
	(-0.54)	(-3.05)	(-1.77)	(-2.52)	(-1.63)
EXP	0.001	-0.000	0.007	0.003	-0.011**
	(-0.35)	(-0.00)	(-1.62)	-0.73	(-2.02)
constant	-1.155***	-2.678***	-0.022	-1.417***	-0.011
	(-9.11)	(-12.39)	(-7.15)	(-0.16)	(-1.73)
N	746		686		376
AIC	1,321.0		1,410.0		767.2
BIC	1,367.2		1,455.4		806.5

Notes: z statistics in parentheses. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

does not have a significant impact on the transition of firms along different stages of technological capabilities.

4.6 Conclusions

This chapter proposes a latent transition analysis model to analyze the dynamics of technological capabilities for a large group of firms. The model is applied to identify the dynamic patterns of technological capabilities for firms in Eastern European and Central Asian economies, meanwhile it investigate the impact of different channels of foreign technology on the transition of firms over time.

The evidence from firms in Eastern European and Central Asian economies fundamentally confirms the findings from previous case studies with respect to dynamic patterns of firm learning: firms develop their technological capabilities through a set of definable stages from experience-based, to search-based, and then to the research-based level. A comparison analysis across a number of Eastern European and Central Asian economies suggests that Slovenia and Croatia have more advanced level of technological capabilities because they have the relatively large share of firms that possess the research-based level of capabilities, while Azerbaijan and Uzbekistan perform the worst owing to the fact that most of firms in these countries load in the experience-based level. Moreover, the transition analysis reveals a sticky phenomena with respect to the dynamics of technological capabilities: firms tend to stay within their existing level of capabilities, and therefore they need to exert extra effort in order to improve their technological capabilities.

Different channels of foreign technology show diverse impacts on the probabilities of firms to change their technological capabilities. The evidence illustrates that the direct sources of technology are more important for the transition of firms, especially for firms at the lower levels of technological capabilities. More specifically, the usage of technology licenses encourages the transitions of firms at all stages towards more advanced level of technological capabilities. The imported intermediate inputs play significant roles in remaining firms at the advanced level, while FDI is observed to have important influences on the transition probabilities for firms which only have basic technological capabilities. However, the exporting intensity does not show a significant effect on the transition of firms along various stages of technological capabilities.

These findings, however, are based on a relatively short time with a small proportion of repeated observations. Since the enterprise survey is still underway, it is possible to obtain a larger dataset over a longer timeframe for this analysis in future. Country-specific factors, such as trade policy or the investment environment, can also be included to explain the probabilities of firms to change their technological capabilities.

Chapter 5

Conclusions

Conventional theories analyze the origins of trade and its impact on technology diffusion by assuming firms within each industry exhibit the uniform behavior. Those analyses either lead to a country's complete specialization at the industrial level in trade or result in entire technological spillovers within the boundary of a certain industry. These arguments were challenged by the wealth of evidence in the 1990s on the heterogeneous performance of firms in international trade. By analyzing micro-data, these studies document that only a small proportion of firms export within each industry for a wide range of countries and large intra-industry trade volume takes place between similar trade partners. Furthermore, differences in the effort of firms to master the technology are highly persistent. The outcome of these efforts is divergent across firms as well. Firm heterogeneity is then addressed by recent micro-founded theories to be important in understanding trade and learning behavior.

5.1 Research Findings

Following the "new" new trade theory and the Neo-Schumpeterian theory, this thesis studies how firms in developing economies learn the foreign advanced technology and improve their performance in response to international trade. The analysis focuses on the micro-level both theoretically and empirically. More specifically, it investigates (1) whether Chinese firms improve their productivity through exporting and why this is the case; (2) whether the exporting status induces firms to invest in R&D and vice versa, and whether both decisions are complementary in improving the performance of firms; (3) how to identify the dynamics of technological capabilities for a large group of firms and how different channels of foreign technology influence the transitions of firms in Central Asian and Eastern European economies.

The main results are summarized as follows:

The evidence in chapter 2 shows that exporting does not lead to a higher level of productivity for manufacturing firms in China. However, in order to penetrate the international market, firms conduct more product innovations when foreign sales are initiated. The trend does not continue after firms start exporting. These findings are obtained by employing a combination of propensity score matching and difference-in-difference estimation. The method is designed to disentangle the self-selection bias from the post-export effect.

The failure of exporters to improve their productivity can be explained by two factors. On the one hand, labor dominates the expansion of exporters. Compared to the matched non-exporters, exporters experience the faster changes in labor than in value-added and capital. This result implies that the potential export-oriented strategy in China may generate more jobs but not necessarily improve the efficiency of firms. On the other hand, exporters need to invest in R&D in order to absorb the advanced technology available in the international market. The combination of exporting and conducting R&D is positively correlated with the productivity of firms. The presence of R&D investment shows a significantly positive effect on the productivity for both exporters and nonexporter, while the positive effect for exporters is larger than for non-exporters. Moreover, the prominent usage of labor by exporters results in a lower level of productivity than that of non-exporters in labor-intensive sectors. Consequently, these results suggest that lower labor cost may still serve as a fundamental factor in supporting the exporting of Chinese firms.

Chapter 3 provides a more detailed analysis on the decision of firms to export and conduct R&D as well as their impact on the performance of firms. In order to guide the empirical analysis in this chapter, I develop a theoretical model by introducing the decision of firms to invest in R&D and factor endowments into the model of Melitz (2003). This modification emphasizes the importance of a sector's peculiarity in understanding the exporting behavior of Chinese firms and the deliberate effort exerted by firms in learning. The extended model derives two different patterns of the decision of firms to export and invest in R&D with respect to their productivity for sectors with various factor requirements. In relatively factor-abundant sectors, it is possible that less productive firms export and intermediately-productive firms invest in R&D to attain a larger domestic market share, meanwhile most productive firms engage in both exporting and investing in R&D. In relatively factor-scarce sectors, more productive firms export and less productive firms serve the domestic market. Among either exporters or nonexporters, only relatively more productive firms invest in R&D. However, when firms are assumed to make their decisions in two steps, the presence of exporting lowers the productivity threshold needed for firms to start R&D activities because the larger market share through exporting is able to compensate the fixed cost of R&D investment. Moreover, utilizing the supermodularity theory, I prove that R&D investment and exporting have the complementary effect on improving the profits of firms.

The evidence from Chinese manufacturing firms reveals a complementarity between exporting and R&D investment, and highlights the importance of factor endowments in understanding the exporting behavior of Chinese firms. The structural break test confirms different patterns of export between labor-intensive and capital-intensive sectors. In labor-intensive sectors, less productive firms tend to export, while in capital-intensive sectors, productivity does not significantly impact the decision of firms to export. Furthermore, the exporting status increases the tendency of firms to invest in R&D and vice versa. While more productive firms select themselves into conducting R&D activities, the presence of exporting experience decreases the productivity required for firms to start R&D activities. This confirms the prediction of the proposed model. Moreover, the interaction of R&D investment and exporting is identified to complement in improving the productivity of firms using a multinomial treatment effect model in which self-selection bias from different decisions is disentangled through a mixed multinomial logistic regression. These findings hold for both labor productivity and TFP.

The latent transition model proposed in chapter 4 identifies three sequential stages throughout the development of technological capabilities for firms in Eastern European and Central Asian economies. This result fundamentally confirms findings from previous case studies with respect to the dynamic patterns of firm learning: firms develop their technological capabilities through a set of definable stages from the experience-based, to the search-based, and then to the research-based level. The comparison analysis across a number of Eastern European and Central Asian economies indicates that Slovenia and Croatia have more advanced level of technological capabilities because they have the largest share of firms that possess the research-based level of capabilities, while Azerbaijan and Uzbekistan perform the worst owing to the fact that most firms in these countries load in the experience-based level. Moreover, the transition analysis suggests that firms tend to stay within their existing stage of technological capabilities, and therefore they need to exert the additional efforts in order to improve their technological capabilities.

Chapter 4 further investigates the impact of foreign sources of technology on the probabilities of firms to upgrade their technological capabilities by incorporating the different channels of foreign technology into a multinomial logistic regression. These channels include the direct sources of foreign technology, such as FDI, technology licenses and imported intermediate inputs, and the indirect sources, for example, exports. The result suggests that the direct sources of technology are more important for the transition of firms, especially for firms at the lower levels. More specifically, the usage of technology licenses encourages the transition of firms at all stages of technological capabilities towards the more advanced level. The ratio of imported intermediate inputs plays a significant role in keeping firms at the search-based level of technological capabilities and in transitioning of firms towards the research-based level. Furthermore, FDI is observed to have important influences on the transition probabilities for those firms which only have basic technological capabilities. However, the exporting intensity does not show a significant effect on the transition of firms through various stages of technological capabilities.

5.2 Policy Lessons

The analysis of the thesis may derive the following policy lessons. First, it is not wise for China to keep the exchange rate artificially low in the long run.[1] Both the model in chapter 3 and empirical analysis in chapter 2 and 3 reveal that firms in China – a relatively labor-abundant country – have two different strategies to penetrate the export market and expand their revenues: by opting to hire more employees with lower labor cost or by investing in technology to become more productive. The artificially low exchange rate produces a relatively low real wages in China. When the foreign market does not select more productive firms, lower real wages increase the tendency of firms to take advantage of cheaper labor, rather than to improve the productivity. In this case, export-oriented strategy may create more jobs; however, in the absence of R&D investment and the deliberate effort of firms to improve their productivity, trade would reinforce China's comparative advantages towards locally factor-abundant sectors.

[1]Whether RMB is devaluated or not is beyond the scope of this thesis; I only argue that this policy should not be adopted.

Second, and related to the first part, policies designed to stimulate the R&D investment should be combined with preferential policies for exporters. The underlying rationale is that, due to the dominant role of R&D investment in improving the efficiency of firms, and the fact that R&D investment and the exporting experience are complementary in improving the profitability of firms, together these policies could be more effective than they would be separately. For example, the obtainment of export rebates should be contingent on the presence of R&D investment or a specified ratio of R&D investment to sales. In this way, the increasing sales in the export market can help to amortize the R&D expenditures and make the investment more profitable. The investment in R&D in turn improves the productivity of firms and their international competitiveness accordingly, and therefore increases profitability of exporting possibly in non-comparative advantage sectors. Indeed, the comparative advantages may be altered through investment in technology.

Third, it is important for policy-makers to differentiate firms at various developmental stages and understand competitive advantages across sectors. When the technological capabilities of firms are identified as the early stage of development, policy should be in favor of more direct channels of learning and should encourage the indigenous firms to adopt the advanced technology. As for China, the current policy requires the multinational companies and joint ventures to guarantee a certain amount of exporting value when they register to open firms in China. Evidence in chapter 3 reveals that foreign-owned firms have a much higher tendency to export yet the lower tendency to invest in R&D compared to indigenous firms. This indicates that such policy may simply result in the intra-firm trading between FDIs in China and their parent firms abroad, or an inclination for foreign-owned firms to reduce their production costs by making use of cheap labor or resource while transferring the obsolete technology. With rapid growth of the Chinese economy, the policy regarding the registration prerequisite may shift towards more high-tech oriented operations.

5.3 Future Research

As with Melitz's (2003) model, the model proposed in chapter 3 only analyzes the binary decision of firms to export or to conduct R&D. The export intensity or R&D intensity, and their subsequent returns are not covered in the model, which can be analyzed in future. The assumptions of the equal market size and the same *ex-ante* productivity distribution can be relaxed in order to investigate the effect of market size and technology differences on the decisions of firms as well as their subsequent consequences.

The evidence of complementarity between exporting and R&D investment for more economies are to be examined. Labor can be considered as human capital. Differentiating skilled workers from unskilled workers will bring more valuable perception on the performance of exporters because skill-biased technological change might be a response to trade liberalization. The change of labor structures among exporters and non-exporters in China is to be investigated. Case studies on the origins and the orientation of key exporters in certain industries in China should provide valuable insight on channels and mechanism for learning-by-exporting.

Bibliography

Acharya, R. C. and Keller, W. (2009). Technology Transfer through Imports, *Canadian Journal of Economics* **42**: 1411–1448.

Allison, P. D. (1999). Comparing Logit and Probit Coefficients Across Groups, *Sociological Methods Research* **28**(2): 186–208.

Almeida, R. and Fernandes, A. M. (2008). Openness and Technological Innovations in Developing Countries: Evidence from Firm-Level Surveys, *The Journal of Development Studies* **44**(5): 701–727.

Archibugi, D. and Coco, A. (2004). A New Indicator of Technological Capabilities for Developed and Developing Countries (ArCo), *CEIS Research Paper 44*, Tor Vergata University, CEIS.

Atkeson, A. and Burstein, A. T. (2010). Innovation, Firm Dynamics, and International Trade, *Journal of Political Economy* **118**(3): 433–484.

Aw, B. Y. and Batra, G. (1998). Technological Capability and Firm Efficiency in Taiwan (China), *The World Bank Economic Review* **12**(1): 59–79.

Aw, B. Y., Chen, X. and Roberts, M. J. (2001). Firm-level Evidence on Productivity Differentials and Turnover in Taiwanese Manufacturing, *Journal of Development Economics* **66**(1): 51–86.

Aw, B. Y., Chung, S. and Roberts, M. J. (2000). Productivity and Turnover in the Export Market: Micro-level Evidence from the Republic of Korea and Taiwan (China), *World Bank Economic Review* **14**(1): 65–90.

Aw, B. Y., Roberts, M. J. and Winston, T. (2007). Export Market Participation, Investments in R&D and Worker Training, and the Evolution of Firm Productivity, *The World Economy* **30**(1): 83–104.

Aw, B. Y., Roberts, M. J. and Xu, D. Y. (2008). R&D Investments, Exporting, and the Evolution of Firm Productivity, *American Economic Review: Papers and Proceedings* **98**(2): 451–56.

Becker, S. O. and Ichino, A. (2002). Estimation of Average Treatment Effects Based on Propensity Scores, *Stata Journal* **2**(4): 358–377.

Bell, M. and Pavitt, K. (1993). Technological Accumulation and Industrial Growth: Contrasts Between Developed and Developing Countries, *Industrial and Corporate Change* **2**(1): 157–210.

Bell, M. and Pavitt, K. (1995). *Trade, Technology, and International Competitiveness*, 1 edn, World bank, Washington, DC:, chapter The Development of Technological Capabilities, pp. 69–101.

Bernard, A. and Wagner, J. (1997). Exports and Success in German Manufacturing, *Review of World Economics* **133**(1): 134–157.

Bernard, A. and Wagner, J. (2001). Export Entry and Exit by German Firms, *Review of World Economics (Weltwirtschaftliches Archiv)* **137**(1): 105–123.

Bernard, A. B. and Jensen, J. B. (1999). Exceptional Exporter Performance: Cause, Effect, or Both?, *Journal of International Economics* **47**(1): 1–25.

Bernard, A. B., Jensen, J. B., Redding, S. J. and Schott, P. K. (2007a). Firms in International Trade, *Journal of Economic Perspectives* **21**(3): 105–130.

Bernard, A. B., Redding, S. J. and Schott, P. K. (2007b). Comparative Advantage and Heterogeneous Firms, *Review of Economic Studies* **74**(1): 31–66.

Bernard, A. B., Redding, S. J. and Schott, P. K. (2010). Multiple-Product Firms and Product Switching, *American Economic Review* **100**(1): 70–97.

Bertrand, M., Duflo, E. and Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates?, *The Quarterly Journal of Economics* **119**(1): 249–275.

Blundell, R. and Dias, M. C. (2000). Evaluation Methods for Non-experimental Data, *Fiscal Studies* **21**(4): 427–468.

Bustos, P. (2011). Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinean Firms, *American Economic Review* **101**(1): 304–40.

Cantner, U. and Pyka, A. (1998). Absorbing Technological Spillovers: Simulations in an Evolutionary Framework, *Industrial and Corporate Change* **7**(2): 369–97.

Castellani, D. (2002). Export Behavior and Productivity Growth: Evidence from Italian Manufacturing Firms, *Review of World Economics (Weltwirtschaftliches Archiv)* **138**(4): 605–628.

Chung, H., Walls, T. and Park, Y. (2007). A Latent Transition Model With Logistic Regression, *Psychometrika* **72**(3): 413–435.

Clerides, S. K., Lach, S. and Tybout, J. R. (1998). Is Learning By Exporting Important? Micro-Dynamic Evidence From Colombia, Mexico, And Morocco, *The Quarterly Journal of Economics* **113**(3): 903–947.

Cohen, W. M. and Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R&D, *Economic Journal* **99**(397): 569–96.

Costantini, J. and Melitz, M. (2007). *The Organization of Firms in A Global Economy*, Harvard University Press., chapter The Dynamics of Firm-Level Adjustment to Trade Liberalization.

Costantini, J. and Melitz, M. (2008). *The Dynamics of Firm-Level Adjustment to Trade Liberalization*, Cambridge MA: Harvard University Press, pp. 107–141.

Dahlman, C. J., Ross-Larson, B. and Westphal, L. E. (1987). Managing Technological Development: Lessons from the Newly Industrializing Countries, *World Development* **15**(6): 759–775.

De Loecker, J. (2007). Do Exports Generate Higher Productivity? Evidence from Slovenia, *Journal of International Economics* **73**(1): 69–98.

De Long, J. B. and Summers, L. H. (1991). Equipment Investment and Economic Growth, *The Quarterly Journal of Economics* **106**(2): 445–502.

Deb, P. and Trivedi, P. K. (2006a). Maximum Simulated Likelihood Estimation of a Negative Binomial Regression Model with Multinomial Endogenous Treatment, *Stata Journal* **6**(2): 246–255.

Deb, P. and Trivedi, P. K. (2006b). Specification and simulated Likelihood Estimation of a Non-normal Treatment-outcome Model with Selection: Application to Health Care Utilization, *Econometrics Journal* **9**(2): 307–331.

Dosi, G. and Orsenigo, L. (1995). Learning, Market Selection and the Evolution of Industrial Structures, *Small Business Economics* **7**(6): 411–36.

Dosi, G., Fabiani, S., Aversi, R. and Mecci, M. (1994). The Dynamics of International Differentiation: A Multi-country Evolutionary Model, *Industrial and Corporate Change* **3**(1): 225–242.

Dosi, G., Soete, L. and Pavitt, K. (1990). *The Economics of Technical Change and International Trade*, New York University Press, New York.

Dutrenit, G. (2004). Building Technological Capabilities in Latecomer Firms: A Review Essay, *Science Technology and Society* **9**(2): 209–241.

Eaton, J. and Kortum, S. (2002). Technology, Geography, and Trade, *Econometrica* **70**(5): 1741–1779.

Ernst, D. and Kim, L. (2002). Global Production Networks, Knowledge Diffusion, and Local Capability Formation, *Research Policy* **31**(8-9): 1417 – 1429.

Ernst, D., Ganiatsos, T. and Mytelka, L. (eds) (1998). *Technological Capabilities and Export Success in Asia*, number 0415158540 in *Routledge Studies in the Growth Economies of Asia*, Routledge.

Fagerberg, J., Srholec, M. and Verspagen, B. (2009). Innovation and Economic Development, *Working Papers on Innovation Studies 20090723*, Centre for Technology, Innovation and Culture, University of Oslo.

Freeman, C. (1974). *The Economics of Industrial Innovation*, Penguin, Harmondsworth.

Ghironi, F. and Melitz, M. J. (2005). International Trade and Macroeconomic Dynamics with Heterogeneous Firms, *The Quarterly Journal of Economics* **120**(3): 865–915.

Ghironi, F. and Melitz, M. J. (2007). Trade Flow Dynamics with Heterogeneous Firms, *American Economic Review* **97**(2): 356–361.

Girma, S., Greenaway, D. and Kneller, R. (2004). Does Exporting Increase Productivity? A Microeconometric Analysis of Matched Firms, *Review of International Economics* **12**(5): 855–866.

Greenaway, D. and Kneller, R. (2007). Industry Differences in the Effect of Export Market Entry: Learning by Exporting?, *Review of World Economics (Weltwirtschaftliches Archiv)* **143**(3): 416–432.

Greenaway, D. and Kneller, R. (2008). Exporting, Productivity and Agglomeration, *European Economic Review* **52**(5): 919–939.

Greenaway, D. and Yu, Z. (2004). Firm-level Interactions between Exporting and Productivity: Industry-specific Evidence, *Review of World Economics* **140**: 376–392.

Griliches, Z. (1998). *R&D and Productivity: The Econometric Evidence*, number gril98-1 in *NBER Books*, National Bureau of Economic Research, Inc.

Grossman, G. M. and Helpman, E. (1995). Technology and Trade, *in* G. M. Grossman and K. Rogoff (eds), *Handbook of International Economics*, Vol. 3 of *Handbook of International Economics*, Elsevier, chapter 25, pp. 1279–1337.

Hahn, C. H. (2004). Exporting and Performance of Plants: Evidence from Korean Manufacturing, *NBER Working Papers 10208*, National Bureau of Economic Research, Inc.

Harris, R. and Li, Q. C. (2009). Exporting, R&D, and Absorptive Capacity in UK Establishments, *Oxford Economic Papers* **61**(1): 74–103.

Hobday, M. (1995). East Asian Latecomer Firms: Learning the Technology of Electronics, *World Development* **23**(7): 1171–1193.

Hoetker, G. (2007). COMPLOGIT: Stata Module to Compare Logit Coefficients across Groups, Statistical Software Components, Boston College Department of Economics.

Hopenhayn, H. A. (1992). Entry, Exit, and Firm Dynamics in Long Run Equilibrium, *Econometrica* **60**(5): 1127–50.

Isgut, A. (2001). What's Different about Exporters? Evidence from Colombian Manufacturing, *The Journal of Development Studies* **37**(5): 57–82.

Kaldor, N. (1961). *The Theory of Capital*, London, chapter Capital Accumulation and Economic Growth, pp. 177–222.

Keesing, D. B. (1965). Labour Skills and International Trade: Evaluating Many Trade Flows with a Single Measuring Device, *Review of Economics and Statistics* **47**: 287–294.

Kim, L. (1997). *Imitation to Innovation: The Dynamics of Korea's Technological Learning*, Harvard Business School Press, Boston, MA.

Kim, L. and Nelson, R. R. (2000). *Technology, Learning, and Innovation : Experiences of Newly Industrializing Economies*, Cambridge University Press.

Krugman, P. (1994). The Myth of Asia's Miracle, *Foreign Affairs* **73**(6): 62–78.

Krugman, P. R. (1979). Increasing Returns, Monopolistic Competition, and International Trade, *Journal of International Economics* **9**(4): 469–479.

Lall, S. (1992). Technological Capabilities and Industrialization, *World Development* **20**(2): 165–186.

Lall, S. (1998). Technological Capabilities in Emerging Asia, *Oxford Development Studies* **26**(2): 213–243.

Lee, K. and Lim, C. (2001). Technological Regimes, Catching-up and Leapfrogging: Findings from the Korean Industries, *Research Policy* **30**(3): 459–483.

Leontief, W. W. (1958). Factor Proportions and the Structure of American Trade: Further Theoretical and Empirical Analysis: Comment, *The Review of Economics and Statistics* **40**(1): pp. 111–116.

Lileeva, A. and Trefler, D. (2010). Improved Access to Foreign Markets Raises Plant-Level Productivity… for Some Plants, *Quarterly Journal of Economics* **125**(3): 1051–1099.

Lorentz, A. (2004). Sectoral Specialisation and Growth Rate DIfferences Among Integrated Economies, *Computing in Economics and Finance 2004 165*, Society for Computational Economics.

Los, B. and Verspagen, B. (2006). The Evolution Of Productivity Gaps And Specialization Patterns, *Metroeconomica* **57**(4): 464–493.

Lu, D. (2010). *Exceptional Exporter Performance? Evidence from Chinese Manufacturing Firms*, PhD thesis, University of Chigago.

Mayneris, F. (2010). Entry on Export Markets and Firm-Level Performance Growth: Intra-Industrial Convergence or Divergence?, *Working Papers 2010.153*, Fondazione Eni Enrico Mattei.

McFadden, D. and Train, K. (2000). Mixed MNL Models for Discrete Response, *Journal of Applied Econometrics* **15**(5): 447–470.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity, *Econometrica* **71**(6): 1695–1725.

Milgrom, P. and Roberts, J. (1990). Rationalizability, Learning, and Equilibrium in Games with Strategic Complementarities, *Econometrica* **58**(6): 1255–77.

Motohashi, K. (2008). Assessment of Technological Capability in Science Industry Linkage in China by Patent Database, *World Patent Information* **30**(3): 225 – 232.

Nelson, R. R. (1990). U.S. Technological Leadership: Where Did It Come from and Where Did It Go?, *Research Policy* **19**(2): 117–132.

Nelson, R. R. and Norman, V. D. (1977). Technological Change and Factor Mix over the Product Cycle : A Model of Dynamic Comparative Advantage, *Journal of Development Economics* **4**(1): 3–24.

Nelson, R. R. and Pack, H. (1999). The Asian Miracle and Modern Growth Theory, *Economic Journal* **109**(457): 416–36.

Nelson, R. R. and Winter, S. G. (1982). *An Evolutionary Approach to Economic Change*, Belknap Press.

Olley, G. S. and Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry, *Econometrica* **64**(6): 1263–97.

Paliouras, D. (2007). *Comparing Regime-switching Models in Time Series: Logistic Mixture vs. Markov Switching*, Master's thesis, University of Maryland.

Parameswaran, M. (2009). International Trade, R&D Spillovers and Productivity: Evidence from Indian Manufacturing Industry, *The Journal of Development Studies* **45**(8): 1249–1266.

Pérez, C. (2001). Technological Change and Opportunities for Development As a Moving Target, *Cepal Review* **75**: 109–130.

Rabiner, L. R. (1989). A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition, *Proceedings of the IEEE*, pp. 257–286.

Roberts, M. J. and Tybout, J. R. (1997). The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs, *American Economic Review* **87**(4): 545–64.

RodrÌguez, J. L. and RodrÌguez, R. M. G. (2005). Technology and Export behaviour: A Resource-based View Approach, *International Business Review* **14**(5): 539 – 557.

Rosenbaum, P. R. and Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects, *Biometrika* **70**(1): 41–55.

Saggi, K. (2002). Trade, Foreign Direct Investment, and International Technology Transfer: A Survey, *World Bank Research Observer* **17**(2): 191–235.

Silverberg, G. and Verspagen, B. (1994). Collective Learning, Innovation and Growth in a Boundedly Rational, Evolutionary World, *Journal of Evolutionary Economics* **4**(3): 207–26.

Silverberg, G. and Verspagen, B. (1995). An Evolutionary Model of Long Term Cyclical Variations of Catching Up and Falling Behind, *Journal of Evolutionary Economics* **5**(3): 209–27.

Smith, J. A. and Todd, P. E. (2005). Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators?, *Journal of Econometrics* **125**(1-2): 305–353.

Stolper, W. F. and Roskamp, K. W. (1961). An Input-Output Table For East Germany With Applications to Foreign Trade, *Bulletin of the Oxford University Institute of Economics & Statistics* **23**(4): 379–392.

Tatemoto, M. and Ichimura, S. (1959). Factor Proportions and Foreign Trade: The Case of Japan, *The Review of Economics and Statistics* **41**(4): pp. 442–446.

Teece, D. J., Pisano, G. and Shuen, A. (1997). Dynamic Capabilities and Strategic Management, *Strategic Management Journal* **18**(7): 509–533.

Todd, P. E. (2008). Matching Estimators, *in* S. N. Durlauf and L. E. Blume (eds), *The New Palgrave Dictionary of Economics*, Palgrave Macmillan, Basingstoke.

Trefler, D. (2004). The Long and Short of the Canada-U. S. Free Trade Agreement, *American Economic Review* **94**(4): 870–895.

Van Beveren, I. (2007). Total Factor Productivity Estimation: A Practical Review, *LICOS Discussion Papers 18207*, LICOS - Centre for Institutions and Economic Performance, K.U.Leuven.

Van Biesebroeck, J. (2005). Exporting Raises Productivity in Sub-Saharan African Manufacturing Firms, *Journal of International Economics* **67**(2): 373–391.

Visser, I. and Speekenbrink, M. (2010). depmixS4: An R-package for Hidden Markov Model, *Journal Statistical Software*.

Visser, I., Raijmakers, M. E. J. and van der Maas, H. L. J. (2009). *13 Dynamic Process Methodology in the Social and Developmental Sciences*, number 978-0-387-95921-4 (Print), Springer New York, chapter Hidden Markov Models for Individual Time Series, pp. 269–289.

Wagner, J. (2007). Exports and Productivity: A Survey of the Evidence from Firm-level Data, *The World Economy* **30**(1): 60–82.

Wagner, J. and etc. (2007). Exports And Productivity - Comparable Evidence for 14 Countries, *Working Paper Series in Economics and Institutions of Innovation 110*, Royal Institute of Technology, CESIS - Centre of Excellence for Science and Innovation Studies.

Wang, F. and Xu, Z. (2011). More Exporting, Less Efficiency? – Why Chinese Exporters Are Not Generating Higher Productivity, *Technical report*, Friedrich Schiller University Jena.

Winter, S. G. (2003). Understanding Dynamic Capabilities, *Strategic Management Journal* **24**(10): 991–995.

Appendix A

More Exporting, Less Efficiency?

A.1 Exports across Industries

The magnitudes of exports are quite uneven across industries. Exports in ICT explode between 2000 and 2007, reaching to 3.74 trillion RMB (492 billion USD, right axis in Figure A.1) in 2007. It is far ahead of other industries, in terms of both the absolute export value and the growth rate, followed by electrical machines and equipments with 0.54 trillion RMB (70.7 billion USD) and vehicles with 0.40 trillion RMB (52.1 billion USD).

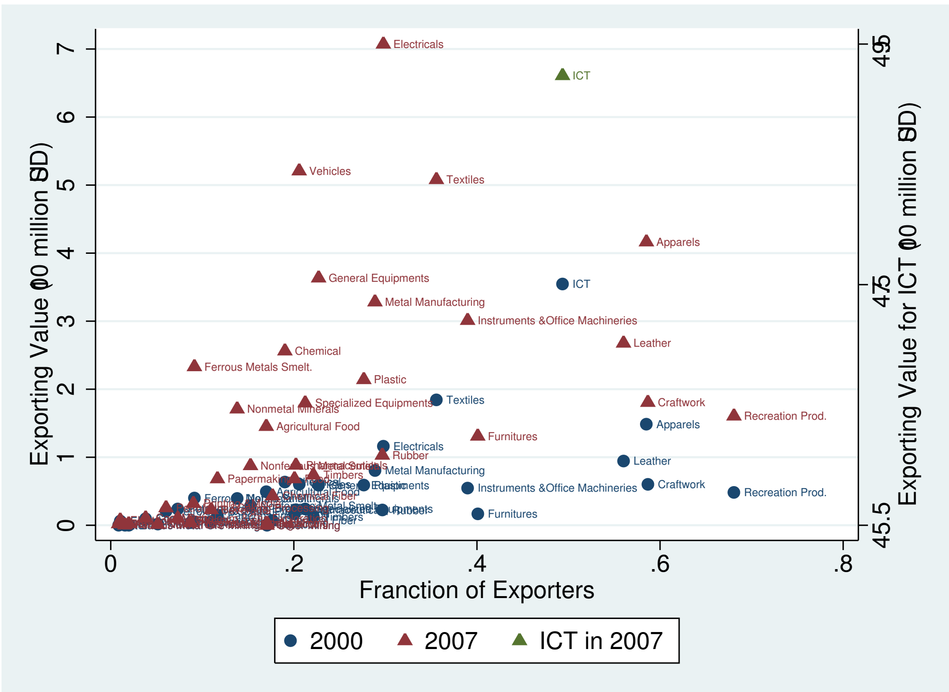
A.2 Preliminary Analysis

A.3 Results

Table A.1: Cross-correlation Table

	EXP	EXV	LPV	CAP	LAB	WAG	INV	SAL	OUP	NPR
EXP	1.000									
EXV	0.069	1.000								
LPV	-0.031	0.037	1.000							
CAP	0.117	0.075	0.135	1.000						
LAB	0.261	0.087	-0.225	0.603	1.000					
WAG	0.307	0.099	0.052	0.607	0.826	1.000				
INV	0.172	0.056	0.236	0.487	0.407	0.492	1.000			
SAL	0.221	0.113	0.537	0.582	0.592	0.701	0.496	1.000		
OUP	0.220	0.113	0.543	0.586	0.595	0.700	0.495	0.993	1.000	
NPR	0.102	0.030	0.053	0.093	0.084	0.125	0.158	0.115	0.116	1.000

Notes: All variables are in logarithmic form except for the export dummy (EXP). All estimates are significant at 0.001 level.



Notes: Exports of ICT in 2007 is shown on the right axis due to its huge magnitude discrepancy with other industries.

Figure A.1: Fraction of Exporters and Export Values by Industry

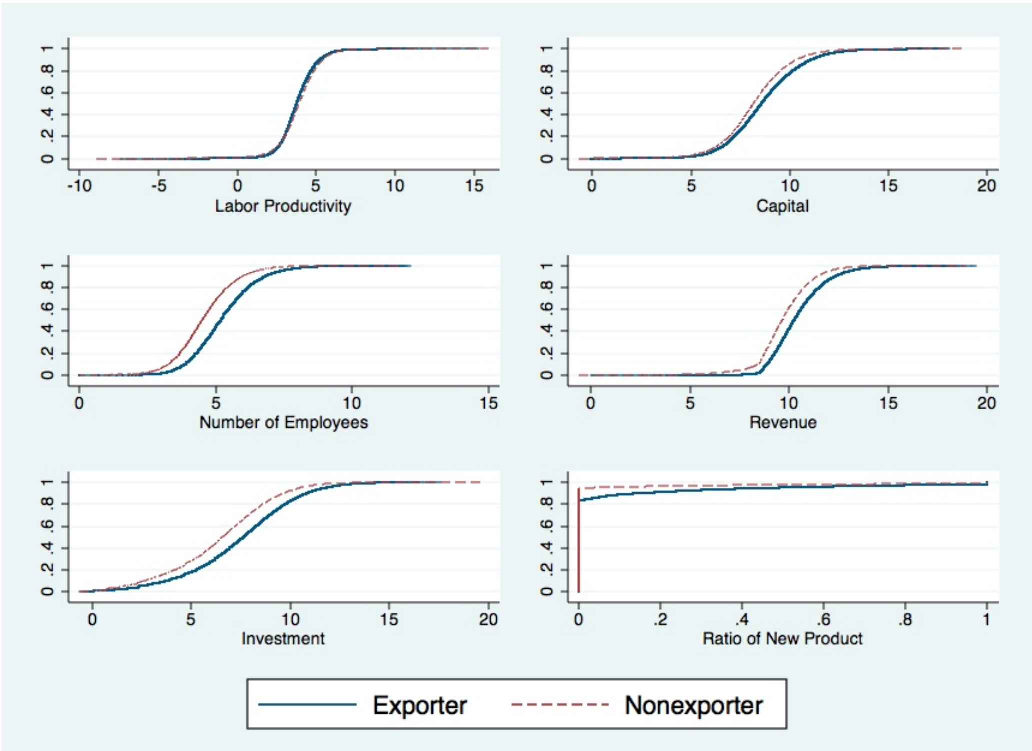


Figure A.2: Cumulative Distribution of Firm Characteristics: Exporter *vs.* Non-exporter

Table A.2: PSM-DiD Estimates by Industry: TFP

Industry	K/L	Starter	β_{DID0}	S.E.	β_{DID1}	S.E.	β_{DID2}	S.E.	β_{DID3}	S.E.	β_{DID4}	S.E.	β_{DID5}	S.E.
Petrol. Explor.	5.19	6	-0.805	1.09	1.356		1.984							
Tobacco	5.00	55	0.023	0.12	0.133	0.09	0.147	0.18	-0.133	0.27	-0.506	0.52	-0.443	0.51
Chemical Fiber	4.54	172	0.123	0.20	0.09	0.069	-0.033	0.33	0.046	0.28	0.716*	0.44	0.924	
Pharmaceuticals	4.27	742	-0.018	0.06	-0.003	0.04	0.069	0.09	-0.052	0.24	0.019	0.30	-0.780*	0.46
Petro. Proc.	4.18	109	-0.016	0.12	0.402	0.39	0.220	0.12	0.588**	0.29	-0.047	0.76		
Beverage	4.17	351	0.095	0.07	0.109**	0.06	0.144*	0.10	0.286**	0.13	-0.020	0.14	-0.124	0.19
Printing	3.97	470	0.084	0.12	0.016	0.10	0.116	0.08	-0.042**	0.14	-0.112	0.18	-0.518***	0.20
Agricultural Food	3.88	1,563	0.023	0.06	0.136	0.10	0.072	0.07	0.180	0.18	0.088	0.23	-0.027	0.33
Food	3.86	795	-0.017	0.10	0.099	0.11	0.023	0.26	0.449	0.15	0.728	0.44	2.23***	0.44
Chemicals	3.82	2,442	0.021	0.03	0.035	0.05	-0.016	0.12	0.081	0.12	0.038	0.16	0.147	0.25
Papermaking	3.82	690	0.101*	0.06	0.046	0.06	0.254***	0.06	0.298*	0.17	0.419	0.34	0.486	1.26
NonM Mnrl.	3.81	2,279	0.040	0.04	0.049	0.07	0.077***	0.02	0.060	0.15	0.074	0.15	0.139	0.20
ICT	3.80	1,741	0.074	0.05	0.022	0.10	0.009	0.06	0.116	0.13	0.206	0.21	0.584	0.36
FM Smelt.	3.76	564	0.032	0.07	-0.056	0.06	-0.102	0.17	-0.215	0.17	-0.406	0.27	0.378	0.51
Vehicles	3.70	1,785	0.081	0.05	0.017	0.03	0.020	0.07	0.181*	0.10	0.176**	0.09	0.351	0.35
Non-FM Smelt.	3.68	696	0.127	0.09	-0.090	0.12	0.023	0.14	-0.087	0.19	-0.072	0.26	-0.356	0.37
Plastic	3.63	1,850	0.025	0.09	0.017	0.04	0.067	0.08	-0.015	0.15	-0.068	0.17	-0.563*	0.31
Specialized Equip.	3.61	1,787	0.005	0.06	-0.014	0.05	-0.048	0.09	-0.102	0.13	-0.045	0.12	-0.165	0.12
Textiles	3.57	3,601	0.042	0.05	-0.018	0.01	0.039	0.03	0.103	0.14	0.009	0.06	-0.094	0.25
FM Min.	3.55	30	-0.360	0.28	-0.161**	0.08	-0.184	0.74	0.765	0.20	0.567			
General Equip.	3.51	2,930	0.087**	0.04	-0.004	0.02	0.082**	0.04	0.131	0.11	0.080	0.10	0.102	0.15
Rubber	3.49	510	-0.115	0.13	-0.197	0.17	-0.290***	0.10	-0.120	0.17	-0.052	0.23	-0.088	0.74
Electricals	3.49	2,537	0.029	0.06	-0.028	0.03	-0.078	0.06	-0.227***	0.05	-0.194	0.17	-0.313***	0.06
NonM-M Min.	3.46	151	0.005	0.19	0.283***	0.11	0.192***	0.06	0.199	0.48	0.281	0.49	0.429	0.72
NonF-M Min.	3.42	80	0.283	0.25	-0.441*	0.26	-0.122	0.18	-0.185	0.32	0.403***	0.04	0.345	

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Table A.2 – Continued

Industry	K/L	Starter	β_{DID0}	S.E.	β_{DID1}	S.E.	β_{DID2}	S.E.	β_{DID3}	S.E.	β_{DID4}	S.E.	β_{DID5}	S.E.
Instruments	3.42	696	-0.002	0.05	-0.069	0.06	0.016	0.07	-0.005	0.16	0.082	0.39	-0.526	0.58
Mtl Manufac.	3.41	2,148	0.103	0.03	0.060	0.06	-0.007	0.12	0.036	0.13	0.209	0.16	0.072	0.26
Timbers	3.36	869	0.044	0.09	0.015	0.11	0.101	0.16	0.090	0.10	0.297	0.33	0.434***	0.18
Furnitures	3.31	607	0.259	0.17	0.191	0.17	-0.170	0.21	-0.223	0.53	-0.572***	0.22	0.190	0.57
Coal Min.	3.02	240	0.129**	0.05	-0.048	0.09	-0.185*	0.10	0.058	0.16	0.134	0.23	0.106	0.43
Recreation	2.86	680	0.014	0.15	-0.025	0.37	-0.033	0.15	0.602**	0.28	0.913**	0.41	1.313	0.00
Craftwork	2.81	1,184	0.112	0.14	-0.109	0.19	-0.181	0.16	-0.295	0.24	-0.264	0.49	-0.121	0.37
Leather	2.68	1,398	0.058	0.06	0.176	0.15	0.011	0.25	0.147	0.28	0.449	0.55	1.551***	0.54
Apparels	2.59	2,824	0.079	0.07	-0.132	0.10	-0.058	0.06	-0.107	0.16	-0.289	0.47	0.292	0.33

*Note: Bootstrapping standard error. Significance level * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$*

Table A.3: PSM-DiD Estimates by Industry: Ratio of New Product Value to Output

Code	Industry	K/L	β_{DID0}	S.E.	β_{DID1}	S.E.	β_{DID2}	S.E.	β_{DID3}	S.E.	β_{DID4}	S.E.	β_{DID5}	S.E.
7	Petrol. Explor.	5.19	0.02	0.01	-0.02		-0.03							
16	Tobacco	5.00	0.02	0.02	0	0.02	0.058***	0.02	0.192***	0.08	0.03	0.04	0.04	0.05
28	Chemical Fiber	4.54	0.040**	0.02	-0.055**	0.03	0.03	0.05	0.22	0.20	0.14	0.26	0.5	
27	Pharmaceuticals	4.27	0.02	0.02	0	0.02	-0.01	0.03	-0.064***	0.01	-0.051*	0.03	-0.094*	0.06
25	Petroleum Proc.	4.18	0.020***	0.01	-0.02	0.01	0.02	0.03	0.04	0.21	0.05	0.24		
15	Beverage	4.17	0.02	0.01	0.01	0.01	0.02	0.02	0.052*	0.03	0.066***	0.02	0.04	0.02
23	Printing	3.97	0.02	0.03	-0.01	0.02	0	0.04	-0.01	0.01	-0.02	0.01	0.06	0.06
13	Agricultural Food	3.88	0.026***	0.01	0	0.00	-0.011**	0.01	0	0.01	0.01	0.01	-0.04	0.02
14	Food	3.86	0.028***	0.02	-0.01	0.03	-0.02	0.02	0.01	0.05	0.03	0.04	0.111**	0.04
26	Chemicals	3.82	0.033***	0.00	-0.018*	0.01	-0.01	0.01	0.01	0.01	0.01	0.01	0.0382***	0.01
22	Papermaking	3.82	0.02	0.02	0.02	0.00	-0.01	0.01	0	0.01	-0.020***	0.01	-0.03	0.09
31	Non-MM	3.81	0.024**	0.01	0	0.00	0	0.01	0	0.01	0	0.02	0.08	0.07
40	ICT	3.80	0.062**	0.03	0.02	0.02	0.01	0.04	0.03	0.05	0.114***	0.03	0.06	0.07
32	FM Smelt.	3.76	0.035***	0.01	0	0.01	0	0.02	-0.01	0.03	0.04	0.06	-0.21	0.18
37	Vehicles	3.70	0.032**	0.01	0.01	0.02	0.02	0.02	0	0.02	-0.03	0.03	0.06	0.05
33	Non-FM Smelt.	3.68	0	0.01	0	0.01	0.03	0.02	0.073**	0.03	0.06	0.14	0.23	0.17
30	Plastic	3.63	0.01	0.02	0	0.01	-0.023**	0.01	-0.04	0.03	-0.05	0.06	-0.086*	0.05
36	Specialized Equip.	3.61	0.048***	0.02	-0.01	0.01	-0.02	0.01	-0.02	0.02	-0.03	0.02	-0.05	0.06
17	Textiles	3.57	0.0127**	0.01	0.01	0.01	0.030***	0.01	0.068***	0.02	0.073***	0.02	0.156***	0.03
8	FMO Min.	3.55	0.21	0.18	-0.017*	0.01	-0.06	0.02	-0.06	0.06	-0.13			
35	General Equip.	3.51	0.037***	0.01	-0.009*	0.01	-0.01	0.02	0.022**	0.01	0.03	0.02	0.01	0.04
29	Rubber	3.49	0	0.01	-0.01	0.02	0.02	0.02	-0.03	0.03	0.01	0.03	0.09	0.06
39	Electricals	3.49	0.02	0.01	-0.01	0.02	0.01	0.03	0.01	0.02	0.02	0.04	0.05	0.04
10	NonM Min.	3.46	0.02	0.02	0.01	0.01	0	0.01	0	0.00	0	0.00	-0.01	0.02
9	Non-FM Min.	3.42	0.06	0.07	0	0.01	-0.1	0.06	0.01	0.01	0	0.00	0	

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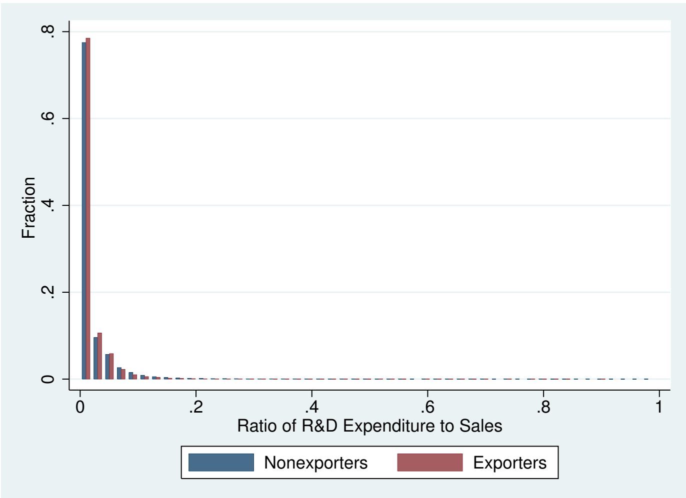
Table A.3 – Continued

Code	Industry	K/L	β_{DID0}	S.E.	β_{DID1}	S.E.	β_{DID2}	S.E.	β_{DID3}	S.E.	β_{DID4}	S.E.	β_{DID5}	S.E.
41	Instruments	3.42	0	0.03	0.01	0.03	0.03	0.03	0.06	0.07	0.02	0.08	-0.18	0.22
34	Mtl. Manufac.	3.41	0.028***	0.01	-0.019*	0.01	-0.027**	0.01	-0.04	0.03	-0.06	0.04	-0.03	0.04
20	Timbers	3.36	0.02	0.01	0.011***	0.00	-0.02	0.03	-0.04	0.03	-0.06	0.04	0	0.00
21	Furnitures	3.31	0.007***	0.03	0.02	0.01	0.03	0.02	0.05	0.08	-0.02	0.11	-0.24	0.18
6	Coal Mining	3.02	0.021***	0.01	0.014***	0.01	-0.02	0.01	-0.04	0.03	-0.05	0.03	-0.05	0.03
24	Recreation	2.86	0.028***	0.01	-0.028***	0.01	-0.04	0.04	0.1	0.08	-0.01	0.03	-0.23	0.00
42	Craftwork	2.81	0.033**	0.02	-0.01	0.02	-0.01	0.03	0.01	0.02	-0.03	0.02	-0.02	0.03
19	Leather	2.68	0.03	0.04	0	0.02	0.021*	0.01	0.03	0.02	0.060*	0.03	0.07	0.06
18	Apparels	2.59	0.014**	0.01	-0.01	0.02	-0.03	0.02	-0.03	0.03	-0.052**	0.03	-0.04	0.11

Note: Bootstrapping standard error. Significance level * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

A.4 R&D Investment

(a) Fraction of R&D Investors among Exporters and All Firms



(b) Histogram of R&D Intensity among Exporters and Non-exporters

Figure A.3: Characteristics of R&D Investment

Appendix B

Complementarities Between R&D Investment and Exporting

B.1 Preliminary Evidence

B.1.1 Variables and Measurements

B.1.2 Descriptive Statistics

Table B.1: Variables and Measurements

Variables	Explanations and Measurements
export	The export dummy with 1 for exporters, and zero otherwise
R&D	The R&D dummy with 1 for R&D investors, and zero otherwise
EXP*R&D	The interaction term of export dummy and R&D dummy
LP	Labor productivity, measured by value-added per worker
TFP	Total Factor Productivity, estimated using the method by Olley and Pakes (1996)
MK/L	The median level of capital-labor ratio within industries
K/L	The capital-labor ratio of firms
avwage	Wages per worker
labor	The number of employees in the logarithmic form
capital	Capital in the logarithmic form
investment	Investment in the logarithmic form
VAD	Value-added of firms in the logarithmic form. It is also considered as profits.
ownership	Four types of ownership are identified through this dummy variable. They are state-owned firms, non-state-owned indigenous firms, foreign-owned firms, and Hong Kong-, Taiwanese- or Macao-owned firms
industry	The industry dummy at the 2-digit level
year	The year dummy

B.2 Model

B.2.1 Autarky

Under autarky, firms maximize their profits by choosing whether to invest in R&D or not ($D = \{0, 1\}$), conditional on the observed productivity φ. The potential profits based on the cost function (3.2) and pricing rule is given by:

$$\pi_i(\varphi) = \begin{cases} \frac{\alpha_i}{\sigma} B[\frac{P_i \rho}{m_i}\varphi]^{\sigma-1} - f_i m_i & \text{if } \{D\} = 0 \\ \frac{\alpha_i}{\sigma} B[\frac{P_i \rho}{m_i}\lambda_i \cdot \varphi]^{\sigma-1} - (f_i + f_{i,r}) m_i & \text{if } \{D\} = 1 \end{cases} \tag{B.1}$$

where $m_i = w^{\theta_i} r^{1-\theta_i}$.

Firm will choose to invest in R&D when $\pi_i\{D = 1; \varphi\} > \pi_i\{D = 0; \varphi\}$. The additional revenue obtained through R&D investment is required to offset the initial fixed costs of R&D investment, as reflected in equation

Table B.2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
LP	889,310	4.15	1.11	-7.40	15.89
TFP	886,678	3.69	1.28	-8.47	11.49
VAD	890,065	8.81	1.40	-.64	18.18
labor	906,427	4.66	1.12	0	12.14
capital	902,141	8.29	1.72	-.71	18.67
wage	903,232	7.22	1.29	-.62	16.16
K/L	901,969	3.63	1.39	-6.78	14.28
avwage	903,172	2.56	.63	-5.46	10.86
investment	82,475	7.12	2.53	-.64	19.73
export	908,517	.26	.44	0	1
R&D	908,517	.10	.30	0	1

Notes: Except for the export and R&D dummy, all variables are in the logarithmic form.

(B.2).

$$\frac{\alpha_i B}{\sigma}(\frac{\rho P_i}{m_i}\varphi)^{\sigma-1}(\lambda_i^{\sigma-1}-1) > f_{i,r}m_i \tag{B.2}$$

Productivity cutoffs

The R&D-investing productivity cutoff in sector i $\varphi_{i,r}$ is the productivity that makes firms indifferent between investing and not investing in R&D with respect to the profits attained.

$$\pi_i\{1;\varphi_{i,r}\} = \pi_i\{0;\varphi_{i,r}\} \iff \varphi_{i,r} = \frac{m_i}{\rho P_i}[\frac{\sigma f_{i,r} m_i}{(\lambda_i^{\sigma-1}-1)\alpha_i B}]^{\frac{1}{\sigma-1}} \tag{B.3}$$

The profits of firms are zero at the exit productivity cutoff φ_i^*,

$$\pi\{0;\varphi_i^*\} = 0 \iff \varphi_i^* = \frac{m_i}{P_i\rho}[(\frac{\sigma f_i m_i}{\alpha_i B})^{\frac{1}{\sigma-1}}$$

The R&D-investing productivity cutoff can be written as the exit productivity cutoff,

$$\frac{\varphi_{i,r}}{\varphi_i^*} = [\frac{f_{i,r}}{(\lambda_i^{\sigma-1}-1)f_i}]^{\frac{1}{\sigma-1}}$$

Given the fixed costs of production and R&D investment, the relative productivity cutoff depends on a sector's technological opportunities and appropriabilities. As λ_i increases, the R&D-investing productivity cutoff will decrease relative to the exit productivity cutoff and a higher fraction of firms will decide to invest in R&D within the sector. When $f_{i,r} > (\lambda_i^{\sigma-1} - 1)f_i$, only the more productive firms conduct R&D. Firms are then partitioned into three groups by the productivity cutoffs, as shown in Figure B.1: firms with productivity less than φ_i^* exit the market; firms with productivity larger than $\varphi_{i,r}$ invest in R&D; other surviving firms do not invest in R&D.

Figure B.1: Productivity Cutoffs

Equilibrium

In order to solve the model, I follow similar steps to that of Melitz (2003) and Bustos (2011). Namely, the free entry (FE) and zero cutoff profit (ZCP) expressed in equation (B.4) jointly determine the productivity cutoffs in equilibrium.

$$\begin{aligned} &f_{i,e}m_i = [1 - G(\varphi^*)]\tfrac{1}{\delta}\bar{\pi} \quad (FE) \\ &\pi(\varphi^*) = \tfrac{1}{\sigma}\alpha_i B(\tfrac{P_i\rho}{m_i})^{\sigma-1}\varphi_i^{*(\sigma-1)} - f_i m_i = 0 \quad (ZCP) \end{aligned} \tag{B.4}$$

The expected profits for surviving firms are

$$\bar{\pi}_i = \frac{1}{\sigma}\alpha_i B(\frac{P_i\rho}{m_i})^{\sigma-1}\tilde{\varphi}_i^{\sigma-1} - f_i m_i - f_{i,r}m_i\frac{1 - G(\varphi_{i,r})}{1 - G(\varphi_i^*)} \tag{B.5}$$

where $\tilde{\varphi}_i$ is the *ex post* expected productivity weighted by $\varphi^{\sigma-1}$ and the *ex post* productivity of R&D-investing firms with productivity φ becomes $\lambda_i\varphi$, as shown in equation (B.6) .

$$\tilde{\varphi}_i(\varphi_i^*) = [\int_{\varphi_i^*}^{\varphi_{i,r}} \varphi^{\sigma-1}\frac{g(\varphi)}{1-G(\varphi^*)}\mathrm{d}\varphi + \int_{\varphi_{i,r}}^{\infty}(\lambda_i\varphi)^{\sigma-1}\frac{g(\varphi)}{1-G(\varphi_{i,r})}\mathrm{d}\varphi]^{\frac{1}{\sigma-1}} \quad \text{(B.6)}$$

Both $\bar{\pi}_i$ and $\varphi_{i,r}$ can be expressed as the exit cutoff productivity φ_i^*. First, the *ex post* weighted expected average productivity can be written as the function of φ_i^* and other parameters as follows.

$$\begin{aligned} \tilde{\varphi}_i(\varphi_i^*) &= \tilde{\varphi}_{i,n} + p_{i,r}\tilde{\varphi}_{i,r} \\ &= [\textstyle\int_{\varphi_i^*}^{\varphi_{i,r}} \varphi^{\sigma-1}\frac{g(\varphi)}{1-G(\varphi_i^*)}d\varphi + \int_{\varphi_{i,r}}^{\infty}(\lambda_i\varphi)^{\sigma-1}\frac{g(\varphi)}{1-G(\varphi_{i,r})}d\varphi]^{\frac{1}{\sigma-1}} \\ &= \big[\tfrac{s\varphi_i^{*(\sigma-1)}}{s+1-\sigma}[1-(\tfrac{f_{i,r}}{f_i(\lambda_i^{\sigma-1}-1)})^{\frac{\sigma-1-s}{\sigma-1}} + \tfrac{\lambda_i^{\sigma-1}f_{i,r}}{f_i(\lambda_i^{\sigma-1}-1)}]\big]^{\frac{1}{\sigma-1}} \end{aligned}$$

Then the expected profits of surviving firms can be written as the function of φ_i^* and other known parameters by substituting $\tilde{\varphi}_i$ into the above result.

$$\begin{aligned} \bar{\pi}_i &= \tfrac{f_i m_i}{\varphi*^{\sigma-1}}\cdot\tilde{\varphi}_i^{\sigma-1} - f_i m_i - f_{i,r}m_i\tfrac{1-G(\varphi_{i,r})}{1-G(\varphi_i^*)} \\ &= \tfrac{sf_i m_i}{s+1-\sigma}[\tfrac{\sigma-1}{s} - [\tfrac{f_{i,r}}{f_i(\lambda_i^{\sigma-1}-1)}]^{\frac{\sigma-1-s}{\sigma-1}} + \tfrac{\lambda_i^{\sigma-1}f_{i,r}}{f(\lambda_i^{\sigma-1}-1)}] \\ &\quad -f_{i,r}m_i[\tfrac{f_{i,r}}{f_i(\lambda_i^{\sigma-1}-1)}]^{\frac{-s}{\sigma-1}} \end{aligned}$$

Substituting the result for $\bar{\pi}_i$ into equation (B.4) yields the following productivity cutoff φ_i^*.

$$\begin{aligned} \varphi_i^* = \;& (\delta f_{i,e})^{-\frac{1}{s}}\big[\tfrac{sf_i}{s+1-\sigma}[\tfrac{\sigma-1}{s} - [\tfrac{f_{i,r}}{f_i(\lambda_i^{\sigma-1}-1)}]^{\frac{\sigma-1-s}{\sigma-1}} + \tfrac{\lambda_i^{\sigma-1}f_{i,r}}{f_i(\lambda_i^{\sigma-1}-1)} \\ & -f_{i,r}[\tfrac{f_{i,r}}{f_i(\lambda_i^{\sigma-1}-1)}]^{\frac{-s}{\sigma-1}}\big]^{\frac{1}{s}} \end{aligned}$$

Note that under autarky, the exit cutoff productivity is independent of factor prices. With the assumption that both sectors have the same *ex ante* distribution of productivity, the exit productivity cutoff for firms in two sectors is simply determined by the differences in the level of fixed cost, i.e. the fixed entry cost, the fixed production cost, or R&D investment.

Aggregation

I only consider steady state equilibria in which the aggregate variables stay constant over time. Goods market clearance requires that total industry revenue equals total labor payments and capital return. The factor market clearance requires the total amount of labor and capital in both sectors must be equal to their respective supply.

$$R_i = wL_i + rK_i, \quad L_1 + L_2 = L, \quad K_1 + K_2 = K$$

With free entry and market clearance condition, the entry of firms equals to the exit of firms in stationary equilibrium. The factor returns to capital and labor must equal the difference between aggregate revenues and the profits, $N_i\bar{\pi} = \Pi_i$, where N_i is the number of firms in sector i.

$$N_i = \frac{R_i}{\bar{r}} = \frac{wL_i + rK_i}{\sigma(\bar{\pi} + f_{i,e})} = \frac{\alpha_i(wL + rK)}{\sigma(\bar{\pi} + f_{i,e})}$$

where K and L are exogenously given.

Price index in sector i is $P_i = N_i^{\frac{1}{1-\sigma}} \frac{w^{\theta_i} r^{1-\theta_i}}{\tilde{\varphi}_i \rho}$.

B.2.2 Factor demand condition

According to Shephard's lemma, firms with productivity φ in sector i requires the following amount of labor to complete production:

$$l_i^H(\varphi) = [f_i + \frac{y_{id}^H}{\varphi} + \chi(f_{i,x} + \tau\frac{y_{ix}^H}{\varphi})]\frac{\partial m_i^H}{\partial w^H} = \frac{\theta_i}{w^H}[\rho r_{id}^H(\varphi) + m_i^H f_i + \chi(\rho r_{ix}^H(\varphi) + m_i^H f_{ix})]$$

where $\chi = 1$ if firms export, and zero otherwise. The amount of labor used in the entry process is $L_{ient}^H = f_{i,e} N_{ient}^H \frac{\partial m_i^H}{\partial w^H} = \frac{N_i^H \theta_i \bar{\pi}_i^H}{w^H}$

Combining the demand for the production and the entry process, the total amount of labor used in sector i is

$$L_i^H = \theta_i N_i^H \bar{r}_i^H / w^H = \theta_i R_i^H / w^H$$

A similar process can be used for capital demand. Using factor market-clearing condition, the aggregate revenue and factor demand is

$$w^H L^H = \theta_i R_i^H + \theta_j R_j^H, \quad r^H K^H = (1-\theta_i) R_i^H + (1-\theta_j) R_j^H$$

which yields the expression in equation (3.8).

B.2.3 Proof of relative price index and factor intensity

Proof. Under autarky, according to ZCP condition, the relative price index between two sectors is given by

$$\frac{P_1}{P_2} = \frac{\alpha_1}{1-\alpha_1}\frac{\varphi_2^*}{\varphi_1^*}(\frac{f_2}{f_1})^{\frac{1}{1-\sigma}}(\frac{w}{r})^{\frac{\sigma(\theta_1-\theta_2)}{1-\sigma}}$$

The relative ratio of exit productivity cutoff and the relative level of fixed costs between sectors are equal across two countries. When $\theta_1 > \theta_2$, $\frac{P_1^F}{P_1^H} > \frac{P_2^F}{P_2^H}$ is equivalent to $(\frac{w^F}{r^F})^{\frac{(\theta_1-\theta_2)\sigma}{1-\sigma}} > (\frac{w^H}{r^H})^{\frac{(\theta_1-\theta_2)\sigma}{1-\sigma}}$.

In an open economy framework with transportation costs, the product price charged by firms with the lowest productivity φ_1^* in the home country is not cheaper than the price charged by the foreign exporters.

$$\frac{(w^H)^{\theta_1}(r^H)^{1-\theta_1}}{(\varphi_1^*)^H} \geqslant \frac{\tau(w^F)^{\theta_1}(r^F)^{1-\theta_1}}{\varphi_{1x}^F}$$
$$\frac{(w^F)^{\theta_2}(r^F)^{1-\theta_2}}{(\varphi_2^*)^F} \geqslant \frac{\tau(w^H)^{\theta_2}(r^H)^{1-\theta_2}}{\varphi_{2x}^H}$$

The following expression is achieved by multiplying the above two equations

$$(\frac{w^H}{r^H})^{\theta_1-\theta_2}(\frac{w^F}{r^F})^{\theta_2-\theta_1} \geqslant \frac{\tau^2\varphi_1^{*H}\varphi_2^{*F}}{\varphi_{2x}^H\varphi_{1x}^F} \tag{B.7}$$

According to the expression of productivity cutoffs, equation (B.7) is equivalent to

$$1 > (\frac{\frac{w^H}{r^H}}{\frac{w^F}{r^F}})^{\theta_1-\theta_2} \geqslant \frac{\frac{P_1^H}{P_1^F}}{\frac{P_2^H}{P_2^F}}$$

□

Appendix C

Foreign Sources of Technology on the Dynamics of Technological Capabilities

C.1 Descriptive Statistics

Table C.1: Descriptive Statistics

	Continuous variables					Categorical variables					
Index	SKL	IMP	EXP	FDI		ISO	R&D	JBT	PDI	PCI	TCL
Min	0	0	0	0	Yes	3,073	3,391	7,020	7,655	10,462	876
Mean	0.5	31.4	10.4	10.4	No	15,260	7,088	11,473	10,816	7,996	11,598
Max	1	100	100	100	NA	96	8,034	20	42	55	6,039
SD	0.3	38.1	24.3	27.9	IP*	84					

*Notes: *'IP' denotes 'in process'.*

Deutschsprachige Zusammenfassung

Konventionelle Theorien analysieren die Ursprünge des Handels und seiner Auswirkungen auf die Verbreitung von Technologie durch Unternehmen der jeweiligen Branche, die einem einheitlichen Verhalten folgen. Entweder führt diese Annahme in einem Land zu einer kompletten Spezialisierung des Handels auf industrieller Ebene oder zu vollständigen Technologie-Spillover in einem bestimmten Industriezweig. Durch empirische Studien auf Mikro-Ebene in den 1990igern Jahren zu internationalen Firmen wurden diese Argumente in Frage gestellt. Erstens exportiert nur ein kleiner Anteil von Firmen in viele verschiedene Länder. Zweitens erfolgt ein groes inner-industrielles Handelsvolumen meistens zwischen ähnlichen Handelspartnern. Drittens sind die Unterschiede in den Bemühungen von Firmen ihre Technologie zu beherrschen innerhalb einer Industrie sowie branchenübergreifend persistent. Dementsprechend heben gegenwärtige Studien die Bedeutung von Heterogenität für das Handelsverhalten und Lerneffekte von Firmen hervor.

In Anlehnung an die "neue" New Trade Theorie sowie die Neo-Schumpeter Theorie, untersucht diese Arbeit wie Firmen in Entwicklungsländern von fremdländischen, fortgeschrittenen Technologien lernen und ihre Leistungsfähigkeit als Reaktion auf den Welthandel verbessern. Die Analyse ist auf der Mikroebene angesiedelt. Es wird untersucht, (1) ob chinesische Unternehmen ihre Produktivität durch Exporte steigern and warum das der Fall ist; (2) ob exportorientierte Firmen Entscheidungen in die Investition von F&E veranlassen und ob beide Entscheidungen auf die Unternehmensleistung haben; (3) wie die Veränderung der technologischen Leistungsfähigkeit einer Vielzahl von Firmen identifiziert werden kann und wie unterschiedliche Kanäle fremdländischer Technologie die Firmenentwicklung in den zentral-asiatischen und osteuropäischen Volkswirtschaften beeinflussen.

Die wichtigsten Ergebnisse sind wie folgt zusammengefasst:

Die empirische Studie in Kapitel 2 zeigt das Export nicht zu einem höheren Produktivitätsniveau von verarbeitenden Firmen in China führt. Weiterhin werden mehr Produktinnovationen umgesetzt, falls Unternehmen auf internationale Märkte abzielen. Allerdings bleibt dieser Zusammenhang nicht mehr bestehen, wenn chinesische Firmen beginnen zu exportieren.

Der mangelnde Erfolg von chinesischen Exporteuren bei der Produktivitätssteigerung kann mit zwei Faktoren erklärt werden. Einerseits dominiert speziell in arbeitsintensiven Sektoren die Expansion des Faktors Arbeit durch den Exporteur. Im Vergleich zu Nicht-Exporteuren findet bei Exporteuren eine höhere Veränderung des Faktors Arbeit statt als beim Value Added oder beim Faktor Kapital. Im Allgemeinen kann man bei chinesischen Exporteuren eine überproportionale Erhöhung des Faktor Arbeit im Vergleich zum Faktor Kapital, Umsatz oder Value-Added beobachten.

Diese Ergebnisse deuten an, dass Export zwar mehr Arbeitsplätze schafft, aber nicht zwangsläufig die Produktivität von chinesischen Firmen verbessert. Es gibt augenscheinlich verschiedene Formen des internationalen Markteintritts von Unternehmen: während Exporteure in den arbeitsintensiven Branchen weniger produktiv sind, haben kapitalintensive Exporteure eine vergleichsweise höhere Produktivität.

Kapitel 2 zeigt auerdem, dass bei Exporteuren Investitionen in F&E unterbleiben. Dies ist jedoch zwingend erforderlich um technologisches Wissen auf dem internationalen Markt zu absorbieren. F&E Investitionen und Export haben einen positiven Effekt auf die Produktivität von Firmen.

Kapitel 3 gibt eine detaillierte Analyse zur Entscheidung von Unternehmen zu exportieren und F&E zu betreiben. Ich erweitere das Modell von Melitz (2003) um die Entscheidung von Firmen über deren F&E Investment und Faktorausstattung. Diese Modifikation unterstreicht die Bedeutung sektoraler Gegebenheiten, speziell um das Exportverhalten chinesischer Unternehmen und deren Anstrengungen sich technologisches Wissen anzueignen zu erklären. Das Model leitet zwei verschiedene Verhaltensweisen von Firmen her. In Sektoren in denen Länder komparative Vorteile haben, besteht die Möglichkeit, dass weniger produktive Unternehmen exportieren und produktivere Unternehmen in F&E investieren um höhere inländische Marktanteile zu erzielen. Die produktivsten Firmen verfolgen beide Strategien.

In Sektoren in denen kein komparativer Vorteil herrscht, exportieren die produktiveren Unternehmen und die weniger produktiven bedienen den inländischen Markt. Unter den Exporteuren und Nicht-Exporteuren betreiben nur die relativ produktiveren Unternehmen F&E. Werden Firmenentscheidungen in zwei Schritten zwei Schritten getroffen, dann senkt eine Exportstrategie die Grenzproduktivität für Unternehmen die in F&E investieren in allen Sektoren. Dies kann durch einen höheren Marktanteil der wiederum die Fixkosten des F&E Investments amortisiert erklärt werden. Unter Zuhilfenahme der Supermodularitätstheorie, leite ich her, dass F&E Investitionen und Export zu höheren Firmengewinnen führen.

Das Beispiel von chinesischen Firmen im verarbeitenden Gewerbe zeigt ein Zusammenwirken von Export und F&E Investitionen. Weiterhin wird die Bedeutung der Faktorausstattung für das Exportverhalten chinesischer Firmen hervorgehoben. Diese offenbaren zudem unterschiedliche Entscheidungsmuster bei Exporten, bezogen auf kapital- und arbeitsintensive Sektoren. In arbeitsintensiven Branchen tendieren weniger produktive Firmen zum Export, während es in kapitalintensive Branchen keinen Zusammenhang zwischen Produktivität und Exportentscheidung gibt. Einer höheren Exportquote lässt eine Tendenz zu einer F&E Investition erkennen. Obwohl produktivere Unternehmen in allen Branchen in F&E investieren, mindert Export die Grenzproduktivität für Firmen, die F&E Aktivitäten starten.

Auerdem wird ein Zusammenhang zwischen der Interaktion von F&E Investitionen und Export sowie der Unternehmensproduktivität aufgezeigt, wobei dieses Ergebnis für die Arbeitsproduktivität und TFP gilt.

Das "latent transition model" in Kapitel 4 schätzt drei aufeinander folgendende Stufen in der Entwicklung technologischer Fähigkeiten von Unternehmen aus Übergangs-Wirtschaftssystemen. Hierbei werden die Ergebnisse aus vorangegangen Fall-Studien über dynamische Muster technologischer Fähigkeiten von Unternehmen bestätigt. Demnach durchlaufen Firmen bezüglich der technologischen Leistungsfähigkeit definierbare Stufen, beginnend von erfahrungsbasiert über suchbasiert hin zur forschungsbasierten Ebene. Der Vergleich von technologischer Leistungsfähigkeit in einer Vielzahl von osteuropäischen- und asiatischen Volkswirtschaften zeigt das Unternehmen in Slowenien und Kroatien die höchsten technologische Fähigkeiten haben. Im Vergleich dazu sind Unternehmen aus Aserbaidschan und Usbekistan am schlechtestem entwickelt.

Zudem suggeriert die Transitionsanalyse das die Unternehmen auf ihrem existierenden Niveau stagnieren. Deshalb ist ein zusätzlicher Aufwand für Unternehmen nötig, sodass sich hochentwickelte Technologien angeeignet werden können und die technologischen Fähigkeiten verbessert werden. Weiterhin untersucht Kapitel 4 den Einfluss verschiedener Kanäle ausländischen technologischen Wissens auf die technologischen Fähigkeiten von Unternehmen. Die Ergebnisse zeigen, dass direkte Quellen technologischen Wissens einen starken Einfluss auf die Firmenentwicklung ausüben. Der Import erbrachter Vorleistungen hat eine signifikantere Rolle um die Zwischenstufe der technologischen Fähigkeit zu halten oder eine Firma hin zur höchsten Stufe zu entwickeln. FDI hat einen wichtigen Effekt auf die Transitionswahrscheinlichkeit für solche Firmen, die nur eine niedrige technologische Leistungsfähigkeit besitzen. Lizenzierung beeinflusst die Transition in Richtung höher entwickelter Stufen. Die geschieht in allen Abschnitten der technologischen Leistungsfähigkeit. Export zeigt keinen signifikanten Einfluss auf die Transition der technologischen Leistungsfähigkeit.

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Hiermit erkläre ich,

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- The Application of Technology Roadmap on the Technology Management, Science of Science and Management of Science and Technology, 2007 (5), with Lanxiang Zhao
- Research on the Transforming toward the Knowledge-Centric Organizations, Science Research Management 2007 (5), with Hong Zhou
- Estimation of Technological Progress' Contribution to Economic Growth Based on the Structural Change, Scientific Management Research, 2005 (4), with Jian Xu

Working Paper

- Complementarities between R&D Investment and Exporting: Theory and Evidence from Chinese Firms (Job Market Paper), March 2011
- More Exporting, Less Efficiency? – Why Exporters in China Are Not Generating Higher Productivity, with Zhaoyuan Xu, January 2011
- Foreign Sources of Technology on the Dynamics of Technological Capabilities: A Latent Transition Analysis for Firms in Developing Economies, June 2010

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