Foreign Entry, Competition and Heterogeneous Growth of Firms:
Do we observe "creative destruction" in China?

Paul Deng
Department of Economics
Brandeis University
dengduo@brandeis.edu

Gary Jefferson
Department of Economics
Brandeis University
jefferson@brandeis.edu

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Abstract

In the face of foreign entry, domestic firms may exhibit heterogeneous patterns of response depending on their technological distance from foreign firms. Domestic firms closer to the foreign technology frontier may choose to compete, while firms that are further down on the technology ladder may suffer a "discouragement effect" and lag further behind. In this paper, we test the Schumpeterian idea of "creative destruction" using firm-level data from China's Large and Medium-Size Enterprise (LME) dataset. We find that foreign entry indeed has a heterogeneous impact on the productivity growth of domestic incumbents. Furthermore, we show evidence that foreign-entry also induces a similar heterogeneous pattern in domestic firms' innovation-related activities.

JEL classifications: O3, D21, F23
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1. Introduction

The impact of foreign entry on domestic incumbents is often thought to be homogeneous, at least as so modeled. Theories predict that foreign entry increases the productivity of domestic firms by promoting competition, and the interactions with foreign firms also enable domestic firms to benefit from positive technology spillovers. However, academics and policy makers alike, ever since Alexander Hamilton, time and time again, have warned the potential damages foreign competition could have inflicted upon domestic industries and advocated industrial policies should be in place to protect domestic firms[1]. In this paper, we show that the impact of foreign entry on domestic firms is far more complicated than previously thought. Depending on the technological distance between domestic and foreign firms, foreign entry can have a divergent or *heterogeneous* impact on domestic firms.

We are motivated by Joseph Schumpeter's idea of "creative destruction". In his book "Capitalism, Socialism, and Democracy" (1942), Schumpeter famously wrote:

> The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets….The process of industrial mutations…that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one. The process of Creative Destruction is the essential fact about capitalism.

Schumpeter's idea hinges on his recognition of the heterogeneity of firms, including that some firms are more productive than others. The *dynamism* of creative destruction is the process whereby more productive firms (often newer ones) constantly replace less productive (and older) ones. Our research extends Schumpeter's original idea of creative destruction to an *international context*. Specifically, we not only allow heterogeneity among domestic firms, but also we bring foreign firms into play. We are especially interested in finding out how foreign entry changes the dynamics of strategic interactions between foreign and domestic firms. We define the heterogeneity of domestic firms in

[1] One of the most recent examples is Larry Summers, former US Treasury Secretary. He expressed his suspicion about the benefits of globalization on *Financial Times* (April 27. 2008). He wrote, "I suspect that the policy debate in the US, and probably in some other countries as well, will need to confront a deeper and broader issue: the gnawing suspicion of many that the very object of internationalist economic policy – the growing prosperity of the global economy – may not be in their interests".

terms of their relative technological distance with foreign firms. We hypothesize that the heterogeneity will in turn determine firms' behavior in response to foreign entry: Firms with more advanced technology choose to compete neck-to-neck with foreign firms, while firms with backward technology suffer a "discouragement effect" and lag further behind. We are certainly not the first to incorporate Schumpeter's idea of creative destruction into an empirical study. Aghion et al. (2005b, 2005c, 2006) have done some pioneering works in the field, and our empirical strategy is closely related to theirs.

We test our hypothesis using firm level data of Chinese Large and Medium Enterprises (LME) from 1995 to 2004. China's case is especially interesting for the following two reasons. First, it is one of the world's largest recipients of FDI[2]. Figure 1 shows FDI inflow into China from 1985 to 2005. Since 1995, China's FDI inflow has

[Figure 1 here]

hovered around US $50 billion per year. During the same period, China's GDP per capita increased from $290 in 1985 to $1,450 in 2005, more than quadrupled[3]. Secondly, as the largest developing country, China is of particular interest to us. To understand why, it is important to differentiate the impact of FDI on developed countries versus developing countries. Unlike the optimistic picture of FDI on developed countries[4], empirical studies of the impact of FDI on developing economies yield quite mixed results. As Dani Rodrik (1999) remarks, "Today's policy literature is filled with extravagant claims about positive spillovers from FDI but the evidence is sobering." On one hand, the research by Blomström (1986) on Mexico, Javorcik (2004) on Lithuania, and Hu and Jefferson (2002) on China showed evidence of positive impacts of FDI on domestic firms. And yet on the other hand, the analysis of Haddad and Harrison (1993) on Morocco, Aitken and Harrison (1999) on Venezuela, Djankov and Hoekrnan (2000) on the Czech Republic, and Konings (2001) on Bulgaria, Romania and Poland cast doubt on the positive spillovers. One common feature of the past research is that they all failed to recognize

[2] World Investment Report 2006 ranks China as the third largest FDI recipient after the UK and the U.S. Source: http://www.unctad.org/en/docs/wir2006_en.pdf
[3] In PPP term, China's GDP per capita was $500 in 1985 and $4,100 in 2005 (Source: World Bank).
[4] See the analysis by Globerman (1979), Haskel et al. (2002) and Keller and Yeaple (2003).

the heterogeneity of domestic firms. Domestic firms were uniformly treated as a homogeneous group. We argue in this paper that the analysis of the impact of FDI on developing countries should take a new direction by taking into account of firms' heterogeneity. In our view, this new approach captures the dynamism between foreign and domestic firms more accurately, and offers a potential solution to the empirical puzzle outlined above.

Besides introducing heterogeneity into our model, our paper also differs from the traditional research on FDI by focusing on the competition effect rather than the spillover effect induced by foreign entry. The word *spillover* itself indicates that the relationship between domestic firms and foreign firms is more of *passive* in nature. Under spillover channel in traditional FDI studies, domestic firms benefit from FDI through adopting foreign firm's technology and know-how, or through personnel turnovers by hiring workers who have worked at foreign firms before. As such, past regression models that study spillover effects simply put FDI on the right hand side of the estimation equation. The dynamism associated with foreign entry, however, is quite different. As suggested by Fudenberg and Tirole (1984) in the case of interactions between (domestic) entrants and incumbents, foreign entry is likely to induce *competition* and even alter the competition strategies of domestic incumbents. In this sense, the effect induced by foreign entry is much broader and not limited to the traditional spillover channel. It has a more *active* feature, involving strategic interactions between foreign entrants and domestic incumbents.

To capture this active component, we investigate the effect of foreign entry on domestic firms in several different ways. First, we analyze the effect of foreign entry on domestic firms' productivity growth. But arguably, productivity growth itself can't provide us with enough information on whether the impact of foreign entry comes through spillover channel or competition channel. So to strengthen our case that foreign entry actually alters domestic firms' competitive strategy, we further analyze the effect of foreign entry on the innovation behaviors of domestic firms.

Bertscheck (1995) investigates the empirical relationship between FDI and innovation. He finds that FDI has positive effects on the innovation activity of German domestic firms, because foreign competition pressures domestic firms to perform more efficiently to maintain their market position. To illustrate the relationship between competition, innovation and growth, Aghion and Howitt (1992) develop a growth model based on Schumpeter's idea of creative destruction. Building on that earlier work, Aghion et al. (2005, 2005b, 2005c) find strong evidence that competition discourages laggard firms from innovating but encourages more competitive firms to innovate. In recent trade and globalization literature, various studies analyze the impact of import competition on the domestic industry (Bernard, Jensen and Schott, 2006; Greenaway, Gullstrand and Kneller, 2008). They find that import competition alters domestic industry's competition strategy: for domestic firms that can not compete with foreign firms, they chose to switch industries, change product mix or close down. Our research adopts features of all strands of literature above. We hypothesize that foreign entry promotes competition; in response, domestic firms, depending on their technological distance from foreign firms, alter their competition strategies, and this heterogeneous effect may show up in both productivity growth and innovation activities.

Here is a preview our empirical results. We find strong evidence that foreign entry increases the productivity growth of Chinese firms in general, but that the response of individual domestic incumbents also depends on their technological position relative to foreign competitors. For domestic firms that are closer (farther) to technology frontier, a 1% increase of foreign entry leads to 0.5% *additional* increase (decrease) of TFP growth; On the net, foreign entry has a positive effect on domestic firms' productivity growth: A 1% increase of foreign entry causes 0.67% of TFP growth of domestic firms. But this does not complete our story. Our research further shows that among domestic firms, again depending on their relative technological distance from foreign competitors, those with smaller technological gaps increase their innovation effort, while those with larger technological gaps significantly cut back their innovation activities.

The rest of the paper is organized as follows. In next section, we formulate our empirical model. This is followed by data description in section three and analysis of the empirical results in section four. The final section concludes.

2. Empirical Model

Our empirical methodology is closely related to the recent research by Aghion et al. (2006), where they investigate the foreign entry effect on productivity growth and innovation incentives of incumbent firms in the U.K. However, there are a couple of differences between our research and Aghion's. First, we apply the heterogeneity analysis to a developing country, where the impact of foreign investment often attracts the most interests. Second, because our focus is on China, our estimation technique is quite different when it comes to analyzing innovation behaviors of domestic firms. Firms in developing countries typically have much less capability to innovate, and this is reflected in our data by the excess zero observations for firms with neither R&D expenditures nor patent applications. We use various different estimation methods to deal with this problem.

2.1 Foreign Entry and Productivity Growth

First we test the effect of foreign entry on productivity growth of domestic incumbent firms. To operate in the same direction as Aghion et al. (2006), we specify our model as follows:

$$\Delta LP_{ijt} = \alpha + \beta_1 FE_{jt-1} + \beta_2 Dist_{jt-1} + \beta_3 FE_{jt-1} * Dist_{jt-1} + X'_{ijt-1}\gamma + u_i + \tau_t + \varepsilon_{ijt}, \qquad (1)$$

where i indexes the domestic incumbent firms, j indexes 3-digit industries, and t represents the year from 1995 to 2004. Productivity is measured by labor productivity[5] at firm level, $LP_{ijt} = (VA/L)_{ijt}$, where VA denotes value-added. Growth of labor productivity is simply defined as $\Delta LP_{ijt} = \ln(\frac{LP_{ijt}}{LP_{ijt-1}})$. On the right hand side of equation (1), FE_{jt-1} represents foreign entry rate, $Dist_{jt-1}$ measures technological distance between foreign and domestic firms in the same industry. Both variables are in 1-period lag. To capture the heterogeneous effect of foreign entry on domestic firms, like Aghion et al (2006), we include an interaction term between foreign entry rate and relative

[5] We also test the heterogeneity hypothesis using the growth of capital productivity and TFP as dependent variables later on.

technological distance, i.e., $FE_{jt-1} * Dist_{jt-1}$. The foreign entry rate, technological distance, and their interaction are the key variables on which we focus. In equation (1), Xs is a vector of control variables. These include growth of the capital-labor ratio to control for the capital deepening process, firm size as measured by the firm's total employment to control for scale, and the industry concentration ratio[6] to capture industry-level competition.[7] The error term is structured to include u_i to control for firm-level fixed effects, and year dummy τ_t to control for time-effects.

We measure the foreign entry rate using the following formula[8]:

$$FE_{jt} = \frac{\sum_{i=1}^{N_{jt}} L_{it} * D_{ijt}(Foreign\,\&\,JV, new\_entry)}{\sum_{i=1}^{N_{jt}} L_{it}} \tag{2}$$

where N_{jt} is the total number of firms in the 3-digit industry j at time t. D_{ijt} is a dummy, which assumes the value of one if a foreign firm (including joint ventures) *newly* enters[9] industry j at time t, and zero otherwise. In words, we measure foreign entry by the ratio of labor employment of newly entered foreign firms relative to the total labor employment in the same industry j and year t. We use the ratio of labor productivity between foreign firms and domestic firms in the same industry j, to measure the technological distance (gap):

$$Dist_{jt} = \frac{1}{3}\sum_{z=0}^{2} \ln\left(\frac{VA^F_{jt-z} / L^F_{jt-z}}{VA^D_{jt-z} / L^D_{jt-z}}\right), \tag{3}$$

6 We measure industry concentration ratio (CR) by the share of sales of the top three firms in industry j:

$$CR_{jt} = \frac{\sum_{n=1}^{3} sales_{nj, n \in top3_j}}{\sum_{i=1}^{N} sales_{nj}}$$

7 Both firm size and the industry concentration ratio are logarithm values.

8 To address the concern that the entry measure in equation (2) may not capture the expansion of previously entered foreign firms, we also measure foreign entry by first calculating the change of employment of all foreign firms in each year then dividing the change by total employment in the same industry j at year t. However, the regression results from this alternative measure were not satisfactory.

9 To identify new entry, in our data, we match firms' recorded opening year with their observation year t.

where F and D denotes foreign and domestic, respectively. Foreign firms here include foreign owned and joint ventures between foreign and domestic firms. To mitigate potential measurement error, we use a 3-year moving average of relative labor productivity to construct technological distance $Dist_{jt}$.

Our priori expectations for the three key variables are as follows. Concerning the sign of foreign entry, because results from the aforementioned empirical research were quite mixed, we expect the sign of entry coefficient could either be positive or negative. For technological distance, we expect to see a strong positive coefficient as the advantages of backwardness would suggest that firms with lower productivity should have the capacity to raise efficiency faster than their more productive counterparts. The sign of the interactive term is of major interest. If our hypothesis is empirically valid, we expect to see a negative sign. A negative sign indicates that foreign entry has a divergent effect on domestic firms: in industries with *larger* technological distances between domestic and foreign firms, foreign entry has a *negative* impact on the productivity growth of domestic firms; in industries with *smaller* technological distance with foreign firms, foreign entry has a *positive* impact on the productivity growth of domestic firms.

2.2 Foreign Entry and Innovation

As discussed in section 1, our critical task is to establish the link between foreign entry and domestic firms' *active* response. So the next question we ask is whether foreign entry alters domestic incumbents' innovation behavior. The question is made more interesting once we allow for heterogeneity among domestic firms. While a typical developing economy may not have the innovative capacity to compete in innovation activity with more technology sophisticated foreign firms, in a world of heterogeneous firms, particularly in a large diverse industrial economy such as China, some domestic firms may indeed exhibit significant innovative abilities. A finding of the active interaction between foreign entry and the innovation behavior of domestic firms, would indicate that domestic firms do not *passively* respond to foreign entry threats. Instead, foreign entry alters domestic firms' competition strategies: firms closer to the technological frontier actually may choose to increase their innovation activities to ensure they are better positioned in future competition; by comparison, firms further down the technology ladder may be discouraged by foreign firms and choose to decrease their innovation activities or give up their innovation plan completely and remain in inaction. To test for this active link, we replace the dependent variable, growth of labor productivity, by two different variables measuring innovation activities. The first is R&D intensity as measured by $\ln(RD/VA)_{ijt}$. The other variable we consider is patent applications, denoted by $ptapp_{ijt}$.

The estimation equations we use are similar to equation (1). Specifically, we estimate the following equation on R&D intensity:

$$\ln(RD/VA)_{ijt} = \alpha + \beta_1 FE_{jt-1} + \beta_2 Dist_{jt-1} + \beta_3 FE_{jt-1} * Dist_{jt-1} + X_{ijt-1}^{'}\gamma + u_i + \tau_t + \varepsilon_{ijt}, \quad (4)$$

where RD>0, RD/VA measures R&D intensity in industry j at time t. The control variables Xs are the same as in equation (1), except that growth of capital-labor ratio is replaced by the level of capital-labor ratio. Not all firms engage in R&D, so naturally we observe a large number of firms with zero R&D expenditure. To deal with these excess zeros, we cannot simply delete them because this will introduce selection bias. Instead, we chose to use a Tobit model to estimate equation (4). Then we replace R&D intensity with patent applications. The number of patent applications is a typical count variable, so we use negative binomial (NB) models to estimate the following equation:

$$ptapp_{ijt} = \alpha + \beta_1 FE_{jt-1} + \beta_2 Dist_{jt-1} + \beta_3 FE_{jt-1} * Dist_{jt-1} + X_{ijt-1}^{'}\gamma + \varepsilon_{ijt}. \quad (5)$$

The advantage of the negative binomial model over the Poisson model is that it allows for over-dispersion of the patent applications. In other words, the negative binomial model relaxes the strong assumption in Poisson models that the mean and variance of the count variable need be identical. Similar to the regression on R&D intensity, the data on patent applications also include a large number of zeros. Normal negative binomial models are not sufficient to deal with this issue. To solve this problem, we chose to estimate patent applications using two alternative negative binomial models with excess zeros. We discuss the estimation details in section four. Finally, one special feature about patent application is that compared with R&D intensity, it reflects innovation outcome, not efforts. Firms may react to foreign entry by increasing spending on R&D, but this effort may not show up in patent applications immediately as it takes time to develop patents and the research outcome is often uncertain. Therefore, we might expect patent applications to be less responsive than R&D intensity to foreign competition.

3. Data

The data for this research are drawn from the Survey of Large and Medium Size Enterprises (LME) that China's National Bureau of Statistical (NBS) conducts each year. The average number of firms included in the database is around 22,000. Our own calculation indicates that in 2002, the total output of the firms in LME accounts for 59% of China's total industrial output. We construct an unbalanced panel of manufacturing firms from 1995 to 2004. To show the overall picture of foreign firms in China, we calculate the share of foreign firms in China's manufacturing sector in terms their employment, output and sales in Table 1.

[Table 1 here]

Foreign firms have played a big role in China. They account for 24% of total labor force, 20% of total output, and 25% of total sales in our manufacturing sector sample. To determine whether to include joint ventures into the calculation of the foreign entry rate, we also compare various statistics between the two groups: foreign firms only, and foreign firms with joint ventures included. The table shows that the difference is huge. For example, if joint ventures are included into foreign firms, the foreign employment share jumps to 40%, output share to 40% and sales share to 47%. Since joint ventures are a big part of China's FDI and have had big influence on various metrics, we define foreign firms in our paper as those independently owned by foreign investors plus all the joint ventures between foreign and domestic firms.

Foreign entry rate is another key variable in our estimation. It is defined in equation (2) in section 2. Table 2 lists the top five industries (3-digit) with the highest and the lowest foreign entry rate in 1995 and 2004.

[Table 2 here]

So is foreign entry rate higher in domestic industries with lower productivity? Or the opposite is true? From Table 2, we see that foreign entry rates are the highest in industries such as chemical products, soft drinks, paper, pharmaceuticals, and they are the lowest in textile, telecommunications, steel, leather products. There seems to be no obvious relationship between entry rate and technological gap. Foreign entry rate is also influenced by many other factors, such as government regulation, which may result in different level of entry barrier for different industries. To get an overall picture of foreign entry rate in different time periods, in Figure 2, we plot the average foreign entry rate during 1995-2004 period for every 2-digit manufacturing industry. We find that on average, the highest foreign entry appears in furniture, rubber, oil refinery, wood, metal products, sports products, food and electric equipment. The average entry rate across all industries in the 1995-2004 period is near 1%.

It is implicitly assumed in our paper that foreign firms have higher productivity level than domestic firms. As defined by equation (3), technological gap, $Dist$, is measured by 3-year average of labor productivity of foreign firms relative to domestic firms at 3-digit industry level. A histogram plot of $Dist$ is shown in Figure 3. From the histogram, we notice that not all

[Figure 3 here]

technological distance are positive. This implies that in some industries, foreign firms have lower productivity than domestic firms. This is reasonable because one can not assume all foreign firms enter Chinese market with more advanced technology. Some were just attracted by the cheap labor in China. Our further calculation indicates that the negative technological gap accounts for about 14.2% of total observations.[10] However, in over 85% of industries, foreign firms have relatively higher labor productivity than domestic firms. In Table 3, we list top ten industries with the highest and lowest technological gap. Industries in which foreign firms have the highest technology lead

[10] The technological distance used in our regressions is a 3-year moving average of the variable $Dist$. Since less than 0.1% of total observations are negative by this measure, we include all observations in our estimations and don't differentiate between the two groups, i.e., the positive vs. negative technological distances.

include medical instruments, special equipment, chemicals and automobile. In contrast, Chinese domestic industries have higher productivity in industries such as toys, apparel, textile, leather and home electronics.

[Table 3 here]

Before the formal regression analysis, we are also interested in finding out what the data can tell us about the relationship between productivity growth and the two major explanatory variables: foreign entry and technological distance. Figure 4-1 plots median growth rate of both labor productivity and TFP against lagged foreign entry rate[11]. The relationship is strongly positive and it indicates that foreign entry spurs productivity growth of domestic firms. In Figure 4-2, we plot a similar graph with median productivity growth against lagged technological distance. The relationship is less clear and the graph exhibits a non-linear pattern: notably, technological distance is positively correlated with productivity growth when distance is below the breakpoint, 1.2; afterwards, the correlation turns to negative. This nonlinear pattern gives us hope that by looking at firms with different technological distance with foreign frontier, we might be able to obtain the heterogeneous effect we hypothesized above.

[Figure 4-1, 4-2 here]

Finally, not all firms engage in innovation activities[12]. This is especially true in developing countries like China. Indeed our sample shows that there exist excess zeros in both R&D expenditure and patent applications. Table 4 shows the percentage of firms with R&D expenditure and patent applications. In 2004, only 16% of domestic firms had R&D expenditure, and only 8% domestic firms filed patent applications. As discussed in the previous section, with these excess zeros, normal OLS and count regression models are not suitable. We will further discuss this issue in section four.

[Table 4 here]

[11] Each point on the graph is the *median* of all labor productivity growth numbers that have the same foreign entry rate. Foreign entry rate is divided into ten bands with equal number of observations.
[12] Here we define innovation in a broad sense. We count both R&D and patenting as innovation. We don't differentiate between imitation and real innovation.

4. Empirical Results and Discussions

Table 5 provides the summary statistics for all the variables used in our regressions. The average foreign entry rate at 3-digit industry level is around 0.6%, with the highest entry rate of 19% in paper industry (refer to Table 2). The labor productivity of foreign firms is, on average, higher than domestic firms', and this is reflected in a positive technological distance on average. In some industries however, foreign firms' productivity is lower than that of the corresponding domestic industry. This is evidenced also in Figure 3.

[Table 5 here]

4.1 Foreign Entry and Productivity Growth: the Baseline Models

The regression results of foreign entry's impact on labor productivity growth of domestic firms are presented in Table 6a. In column (1), we first run a simple pooled OLS regression with four explanatory variables: foreign entry, technological distance, their interactive term and growth of capital intensity. The coefficient on technological distance is positive and significant, and the positive sign indicates that firms further from the technology frontier benefit most from *knowledge spillover*, as also evidenced in Griffith (2004). Another possibility is that it simply reflects the "*catch-up effect*": firms further from technological frontier grow faster simply because their starting point is low. The coefficient on growth of capital-labor ratio is also positive and significant and it implies that higher growth of capital per worker leads to higher labor productivity growth. This result again conforms to the standard growth theory. However, in this simplest form of regression, both foreign entry and the interactive term show up to be not statistically significant; the signs of the coefficients are, however, as expected.

[Table 6a here]

In column (2), we include two more control variables: firm scale and industry concentration ratio at 3-digit level. As shown in the table, the coefficient on the interactive term now becomes statistically significant. Also, the coefficients on the two additional control variables are negative and statistically significant. The negative sign on the firm size indicates that larger firms tend to grow slower in productivity; the negative sign on industry concentration ratio shows that higher industry concentration ratio, or less industry competition, often leads to slower productivity growth of the domestic firms.

In column (3) and (4), we run the regressions with same explanatory variables using our preferred specification, i.e., OLS regression with both fixed effects at firm level and time effects. First to note is that the coefficient of foreign entry becomes highly significant in this specification and it suggests that foreign entry has a positive effect on domestic firm's labor productivity growth. The coefficient of the interactive term between foreign entry and technological distance are statistically significant and the sign of the interaction remain negative. As mentioned previously, this interactive term is designed to capture the impact of foreign entry on productivity growth conditional on the technological gap. The negative coefficient directly supports our hypothesis and confirms the previous finding by Aghion et al. that domestic firms exhibit a diverging growth patterns in response to foreign entry, i.e., when facing foreign entry threat, the farther the technological distance, the lower productivity growth of domestic firms[13].

[Table 6b here]

Previously, our dependent variable is growth of *labor* productivity. As argued by many, labor productivity is not an ideal productivity measure because growth of labor productivity may be the result of higher growth of capital-labor ratio. In Table 6a, we control for this problem by including capital intensity as the control variable. In Table 6b, we test our baseline model by replacing growth of labor productivity with total factor productivity (TFP). The TFP estimates use a two-stage approach in which we first

[13] Considering foreign entry rate may be lumpy, we also use an alternative method to measure foreign entry rate. Instead of using annual entry rate, we calculate the three-year moving average of the original entry rate to smooth the potential entry noise. Again, all coefficients remain robust and their signs do not change.

estimate a production function to derive measures of TFP and then use the TFP series in rate-of-change form to estimate the impact of foreign entry on TFP growth. The results for this new set of regressions are reported in Table 6b. Column (1) reports the previous results using growth of labor productivity, gLP, as the dependent variable; these results serve as a benchmark. In columns (2) and (3), we replace gLP with two different TFP growth measures. First, we assume all firms have the same production technology, i.e., the factor output elasticity is the same for all firms. We assume constant return to scale and obtain capital-output elasticity, α , by estimating the following equation:

$$\ln(VA/L)_{ijt} = a_0 + \alpha \ln(K/L)_{ijt} + u_i + \tau_t + \varepsilon_{ijt} . \tag{6}$$

The error term is structured to include u_i for firm-level fixed effects, and year dummy τ_t to control time effects. By our estimation, α =0.23, so labor output elasticity, β =1-0.23=0.77. Finally, we construct TFP using the formula: $TFP_{it} = (VA/K)_{it}^{0.23}(VA/L)_{it}^{0.77}$. The regression results using this TFP measure is reported in column (2). Again, the coefficients for all independent variables remain the same sign and statistically significant as before.

Next, in column (3), we relax the strong assumption that all firms have the same production technology, and we assume firms in the *same industry* have the same production function. We obtain capital-output elasticity, α_j , by estimating equation (6) for each 2-digit industry. And we then use the following formula to construct our second TFP measure: $TFP_{it} = (VA/K)_{it}^{\alpha_j}(VA/L)_{it}^{1-\alpha_j}$. The regression results again remain robust and similar to the results in column (1) and (2)[14]. So how to interpret these results? We use column (3) as an example to explain our findings. The coefficient of foreign entry, 1.243, indicates that a 1% increase of foreign entry in previous year correlates with a

[14] We also calculated TFP by assuming every firm has its individual production technology. We do so by first computing firm-level labor income share, $\alpha_L = (wage + welfare)/VA$, then we arrive TFP using $TFP_{it} = (VA/K)_{it}^{1-\alpha_{L,it}}(VA/L)_{it}^{\alpha_{L,it}}$. Foreign entry still has a positive impact of TFP growth and the coefficient of interactive term between foreign entry and technological distance is again negative and statistically significant.

1.24% increase of TFP growth on average. On the impact of technological distance, the highly robust positive coefficient indicates that with 1% increase of the technological gap, as measured by relative productivity between foreign firms and domestic firms, TFP tends to grow 1.79% faster. The most interesting result is the coefficient on the interactive term. The number, -0.578, indicates that with foreign entry rate fixed, a1% increase of the technological gap decreases domestic firms' productivity growth by 0.58%. Similarly, a 1% decrease of the technological gap leads to a 0.58% gain of productivity growth. In other words, foreign entry has a heterogeneous effect on domestic firms productivity growth depending on the technological gap between domestic firms and foreign firms.

[Table 6c here]

In Table 6c, we use an alternative specification of estimation equation to further illustrate the heterogeneous impact of foreign entry. We replace the *continuous* technological distance variable $Dist_{jt-1}$ in the interactive term with newly created *categorical* dummies, $D\_fardist_{jt-1}$ and $D\_neardist_{jt-1}$. The purpose of this exercise is to demonstrate the heterogeneous patterns in a simpler and clearer fashion. The dummies are created in the following manner: If $Dist_{jt}$ is above the median value of technological distances in year t, $D\_fardist_{jt}$ =1; otherwise, $D\_neardist_{jt}$ =1. The new results are recorded in column (2), (3), (5) and (6). We use column (1) and (3) from previous tables as the benchmark. Compared to the coefficient of the previous interactive term, the dummy interaction term gives us an easier interpretation. For example, in column (5), the negative coefficient of -0.542 indicates that for the domestic firms on the lower half of the technology ladder, foreign entry tends to decrease their TFP growth by 0.54% percent on average. For those domestic firms that are closer to the technological frontier, the upper half on technology ladder in their corresponding industry, foreign entry has the exact opposite effect: It increases their TFP growth rate by 0.54%. The next natural question to ask is: what is the *net* effect of foreign entry on the productivity growth of those laggard firms? The answer to this question has important policy implications as it helps us gauge the overall effect that foreign entry has on a developing country like

China. In column (4), we obtain this net effect by adding up the coefficients of foreign entry and the interactive term. The sum of the two coefficients remains positive 0.665 (=1.243-0.578), and this implies that foreign entry on average has a *net* positive effect on the productivity growth of laggard domestic firms.

Summarizing results from tables 6a to 6c, we conclude that the heterogeneous effect of foreign entry on domestic firms' productivity growth is highly significant and remains robust throughout. The results are not subject to the choices of productivity measures, be it labor productivity, capital productivity or total factor productivity. On the impact of foreign entry, if we just look at foreign entry rate alone, other things being equal, our results show that foreign entry has a significant positive impact on firms' productivity growth. Similarly, firm's technological distance with the frontier also helps to determine firm's productivity growth: the larger the technological gap, the faster the productivity growth. The coefficients of the two major control variables are also interesting. First, the size of the firm tends to depress productivity growth. Second, industry concentration level has significant impact on productivity growth: the higher the concentration ratio (or less industry level competition), the lower the productivity growth.

4.2 Foreign Entry and Productivity Growth: Estimation Issues and Extensions

In this section we discuss various estimation issues and address several concerns from our previous estimation. We first consider the potential selection bias resulting from firms' entry/exit. Then we address the concern that our explanatory variables might be endogenous. Finally we test a stricter heterogeneous effect of foreign entry at the firm level.

4.2.1 Selection Bias

Our calculation shows that in our unbalanced panel dataset, roughly 22% of firms each year dropped out. If firm's exit is a result of lower productivity, the firms left in the sample tend to be more productive. This may cause a selection bias for our previous estimation.   To deal with this potential problem, we follow the estimation method outlined in Wooldridge (2002). The estimation procedure is similar to the Heckman twostep selection procedure. The difference is that it extends Heckman's method to the panel data setting, in which selection bias may appear each year sequentially.

We first run a probit model for each period: $s_{i,t+1} = 1[w_{it}\delta_t + v_{it} > 0]$, where v_{it} is error term and $v_{it} \sim N(0,1)$; w_{it} includes variables that explain firm's exit decision. In our case, w_{it} includes firm's productivity level measured by TFP and a dummy variable indicating whether firm i is profitable in year t. We calculate inverse mills ratio, λ_{it}, for every period and then estimate the following equation:

$$y_{it} = x_{it}\beta + \rho_2 d2_t \hat{\lambda}_{it} + ... + \rho_T dT_t \hat{\lambda}_{it} + u_i + \tau_t + \varepsilon_{ijt}, \quad t \geq 2. \tag{7}$$

Here x_{it} includes foreign entry, technological distance, their interactive term and all other control variables as in equation (1). u_i, τ_t again are firm-level fixed effects and time effects. To deal with selection bias from multiple periods, equation (7) includes inverse mills ratios from all previous periods and differentiates them by using a year dummy dT. For example, $d2_t$ =1 if year=1996 in our sample.

The estimation results after correcting potential selection bias are reported in column (2) and (4) in Table 6d. Compared to previous regression results in column (1) and (3), we find no big change in the coefficients of the explanatory variables. The interactive term, in particular, still remains negative and statistically significant. The magnitude of the negative coefficient becomes a little bigger, however. We think this makes perfect sense: If these dropouts were to stay, we would have more firms with lower productivity in our sample. As such, foreign entry should have a more pronounced heterogeneous effect (or a more negative coefficient) on the productivity growth of domestic firms.

[Table 6d here]

4.2.2 Endogeneity Issues

Our previous OLS regressions with firm fixed effects are based on the assumption that our main variables, foreign entry, technological distance and their interactions, are orthogonal to the error term. This assumption could be violated if 1) foreign firms' entry decision is dependent upon incumbent firms' rate of productivity growth; 2) entry decision depends on the perceived technological distance between foreign and domestic industries; 3) the omitted variables may cause entry, technological gap and productivity growth move in the same direction. In previous section, according to equation (1), we have mitigated this potential endogeneity problem by using one-period lag of all major independent variables, and we also argue in section 4.3 that there exists a systematic response from incumbent firms to the threat of new foreign entry: not only the response shows up in productivity growth, but also in more *active* areas, where domestic firms respond by changing their innovation behaviors. However, despite all efforts to mitigate the potential endogeneity, we feel compelled to address this issue so that we can strengthen our case and make our arguments more persuasive.

New development in econometrics of dynamic panel data model provides us with sufficient tools to address this issue. The traditional method in dealing with endogeneity is to find instrument variables that are assumed to be orthogonal to the error term. However, in most cases, these instrument variables are either hard to come by or they have weak correlation with endogenous variables. Arellano and Bond (1991) solved the problem by introducing GMM-style IVs out of endogenous variable itself. The idea is to treat the lagged terms of endogenous variable itself as instrument variables, assuming these lagged variables are orthogonal to the error term after first differencing. So Arellano-Bond method uses level of lagged variables to estimate first-differenced endogenous variables. As such, this method is often called *difference GMM*. Compared to the method of Anderson and Hsiao (1982), IVs introduced by Arellano/Bond method are arguably more efficient because more than one-period of lags (and often much deeper lags) are used. Blundell and Bond (1998) further advanced dynamic panel data modeling by introducing *system GMM* method, in which IVs from *difference GMM* are stacked with another set of newly created IVs. The new set IVs are created in the following manner: the lags of the potential endogenous variables are first differenced and then used directly as IVs in original estimation equation without differencing. The assumption is that differenced lagged variables are more likely to be orthogonal to the original error term. For this reason, *system GMM* is a method of using lagged differences to estimate levels. In contrast, *difference GMM* is a method of using lagged levels to estimate differences.

We treat our main variables, foreign entry, technological distance and their interactive term, as potentially endogenous. We again estimate equation (1) using both difference and system GMM methods. The previous fixed-effect OLS regressions are used as benchmark. All the results are reported in Table 6e. Column (1) to (3) present results from fixed-effects OLS, Arellano-Bond GMM and Blundell-Bond GMM, respectively, and the dependent variables used here is labor productivity growth (gLP). In column (4) to (6), we present results for the same three methods but use growth of total factor productivity (gTFP) as dependent variable[15].

[Table 6e here]

Once again, the results in column (2) and (3) are very similar to column (1). The heterogeneous effect we hypothesized is still statistically significant and has the correct negative sign. In column (2), Arellano-Bond test of AR(2) autocorrelations is rejected (0.115) and Hansen J-test statistic (0.463) of overall orthogonality of instrument variables is also satisfactory. This is not the case for system GMM estimation in column (3), where only AR(2) test statistic (0.111) is satisfying but IVs are suspected to be not orthogonal to the error term (0.031).

In column (5) and (6), we report regression results using gTFP as dependent variable. The coefficient estimates are very similar, and once again Arellano-Bond method is preferable to Blundell-Bond method. This makes sense as Blundell-Bond System GMM method is more suitable for the case when the dependent variable behaves like random-walk (Roodman 2007). This is not the case for productivity growth where the rate of growth is expected to be strongly correlated with the past. Note that in column (5), we cannot reject AR(2) in error term (0.041) and we chose to mitigate the problem by using deeper lags in our estimation.

[15] Here we only used TFP calculated by assuming firms within the same industry have the same production technology. The other two methods of TFP calculation gave us the similar results.

4.2.3 Stricter Heterogeneity

Finally, in Table 6f, we present yet another set of regression results based on an alternative measurement on technological distance. Instead of using the definition in equation (3)[16], we use the following formula to measure the technological gap:

$$Dist_{ijt} = \frac{1}{3}\sum_{z=0}^{2}\ln\left(\frac{VA_{jt-z}^{F} / L_{jt-z}^{F}}{VA_{ijt-z}^{D} / L_{ijt-z}^{D}}\right), \tag{8}$$

The difference between equation (8) and equation (3) is that in equation (8) the labor productivity of domestic firms is indexed at firm level, i, not on the industry level, j. The regression results again are very similar. In particular, the coefficient of the interactive term between foreign entry and technological distance again is negative and statistically significant[17].

[Table 6f here]

The regression results from this alternative technological distance measurement offer us some very interesting insights. It is essentially a *stricter* version of our hypothesis. Previously, we have confirmed that, facing foreign entry, firms in *industries* that are closer to foreign technology frontier have faster productivity growth, and firms in *industries* that are less technologically advanced suffer slower productivity growth. Now, with results from Table 6f, we can further conclude that not only the heterogeneous effect exists among firms across different industry-level technological distances, but also it exists among firms within the same industry.

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[16] Aghion et al. (2006) uses the same definition, i.e., technological distance is indexed at industry level.

[17] Equation (8) uses 3-year moving average to smooth the potential noise of technological distance at firm level. We also tested an alternative measure of the tech. distance without the smoothing. The advantage of this alternative is we get to keep more observations in the regression. The results remain robust and are similar to the one using smoothing method.

4.3 Foreign Entry and R&D Intensity

As discussed in section 2, we are not only interested in testing the impact of foreign entry on domestic firms through the conventional spillover channel, but also we are interested in finding out the impact through the competition channel. First, we test equation (4) using R&D intensity as the dependent variable. R&D intensity is defined as $\ln(\frac{RD_{ijt}}{VA_{ijt}})$. To prevent creating too many missing observations in our dataset, we set $\ln(\frac{RD_{ijt}}{VA_{ijt}})$ to zero if R&D=0. This formula enables us to keep firms with no R&D expenditure in the sample. The regression results are presented in Table 7.

[Table 7 here]

In column (1), we run a simple OLS regression on three key variables: entry rate, technological distance and their interaction term. The coefficients on all independent variables are statistically significant, and their signs are as expected. Column (2) includes additional control variables plus firm-level fixed effects and time effects. The coefficients on all variables become insignificant. This result is not surprising because OLS is not the ideal estimation method when a big share of dependent variable, R&D intensity, is zero (see Table 4). In column (3) and (4), we use a Tobit model to estimate a truncated sample where R&D intensity assumes only positive values. Our choice of Tobit model adequately addresses the problem of sample selection bias. All variables show up to be statistically significant. In column (4), we include additional control variables. The results remain robust. Foreign entry has a strong positive effect on domestic firms' R&D intensity, higher foreign entry in period t-1 leads to higher R&D intensity of domestic firms in period t. The coefficient on technological distance is also positive and significant. The interactive term again shows up to be negative and significant. It indicates that there exists a similar diverging pattern on domestic firm's R&D intensity. As with productivity growth, this diverging pattern depends on domestic firms' technological gap with foreign firms. Finally, in column (5) and (6), we incorporate random effects into the Tobit model and the results again show up to be significant and all the signs remain unchanged.

These results strongly confirm our hypothesis that not only do domestic firms exhibit a divergent growth pattern in productivity growth, but they also respond actively to foreign entry by increasing or decreasing their R&D spending. Similar to productivity growth, firms closer to the technological frontier increase their R&D expenditure, while firms far behind the technological frontier decrease their R&D spending.

4.4 Foreign Entry and Patent Applications

In this section, we investigate the impact of foreign entry on domestic firms' patent applications. The results are shown in Table 8. In column (1) to (4), we temporarily ignore the problem of excess zeros of patent counts. Column (1) and (2) use negative binomial model; column (3) and (4) estimate negative binomial model with random effects. Although the results are consistent with our previous findings for productivity growth and R&D intensity, due to the issue of excess zeros, we are cautious in interpreting these results. We think the estimation power of these models is questionable if the problem of excess zeros is not addressed. Negative binomial model is capable of accommodating a somewhat thicker tail with many zeros, but in our sample, zero counts of patent applications account for 90% of the total observations. Our estimation strategy is to find a data generation process to model these excess zeros. Following Cameron and Trivedi (2005), there are two options available. One is to use a zero-inflated negative binomial model; the other is to use a hurdle model or a two-part model (2PM). The latter is *more widely* used in econometrics.

[Table 8 here]

We first try zero-inflated negative binomial (ZINB) model. ZINB enables the zero count to occur in two ways. First, the zeros can be incorporated through a binary process. Typically, this binary process can be utilized by either a probit or logit model. Second, more zeros can be generated in the second-stage count process when the binary variable takes unity as its value. So essentially both processes help to generate zeros and that's why it's called zero-inflated. The density of ZINB is as follows:

$$g(y)=\begin{cases} f_1(0)+(1-f_1(0))\cdot f_2(0) & if\ \ y=0 \\ (1-f_1(0))\cdot f_2(y) & if\ \ y\geq 1 \end{cases} \tag{9}$$

Regression models let $f_1(\cdot)$ be a logit model and $f_2(\cdot)$ be a negative binomial density. The estimation results of ZINB model are presented in column (5). In the first stage we run a logit model. Following Blundell et al. (1999), we incorporate two additional variables to help generate zeros. These two variables essentially measure the firm's technological stock. One is firm's previous stock of patent application; the other is a dummy variable capturing whether firm has previously had any patent applications[18]. The coefficients on both variables are highly significant. The negative sign on the patent applications stock implies that firms with more previous patent applications are *less* likely *not* to file for patent applications again. The negative sign on the dummy indicates that firms with no previous patent application record are likely to remain dormant by not filing new patent applications. In the second stage, we plug in our key variables to the negative binomial count regression process. Again, the results show up to be as expected, with the interactive term again being negative and significant.

Next we try our preferred model: the hurdle model or two-part model (2PM). Like ZINB model, hurdle model relaxes the assumption that the zeros and the positive counts come from the *same* data generation process. But unlike ZINB model, hurdle model assumes the second stage data generation process comes from the truncated density $f_2(y\,|\,y>0)=\ f_2(y)/(1-f_2(0))$. So the density of hurdle model typically has the following structure:

$$g(y)=\begin{cases} f_1(0) & if\ \ y=0, \\ \dfrac{1-f_1(0)}{1-f_2(0)}\cdot f_2(y) & if\ \ y\geq 1. \end{cases} \tag{10}$$

[18] Dummy is created in the following way: if at time t, the firm has no patent applications in all previous periods (1,2…t-1), dummy is set to 0; otherwise it's 1.

The hurdle model assumes a two-stage decision-making process. In our context, the hurdle model assumes the decision process to invest in patenting at all is different from the decision process to increase or decrease patenting after firms have already engaged in patenting activities. The firm's first-stage decision process is to choose whether to overcome the innovation *hurdle* by altering their competition strategy and become an "innovative type". The second-stage decision process is concerned with those firms that have had previous patent applications. The decision for these firms to make is to choose whether to engage in more innovation activities or less (or even zero) when facing foreign entry threat. We hypothesize that for the first-stage, firms closer to the technological frontier are more likely to initiate innovation activities while firms far behind are less likely to do so; in the second stage, we expect to see a similar pattern: firms higher on the technology ladder, with previous investments in patenting, choose to increase their patent applications while firms lower on the technological ladder choose to reduce their investment in patenting or totally give up.

The regression results of the hurdle model are presented in column (6). In the first part of the hurdle model, we estimate the likelihood of non-zero patent applications in year t using a logit model after controlling for firms' previous patent stock and whether firms have ever engaged in patent applications. We also create two more interactive terms between foreign entry and previous patent applications and the application history dummy. The results are very interesting. The positive sign on the foreign entry rate indicate that foreign entry induces firms to initiate patent applications[19]. The positive sign on the previous application dummy indicates that firms with patent filing history are more likely to file for patent applications again.

However, the most interesting part of our results lies in the three interactive terms. First the coefficient on foreign entry and technological distance is negative and significant. This again confirms our hypothesis that foreign entry produces a divergent effect on domestic firms innovation behavior. Second, the coefficient of the interaction between foreign entry and the previous stock of patent applications shows up to be positive and significant, which indicates that firms with more patent applications in the

[19] Hu and Jefferson (2008) showed the similar result that foreign direct investment has been a major source of recent increasing domestic patent applications.

past are more likely to file for patent applications when facing the threat of foreign entry. Third, the coefficient of the interactive term between foreign entry and the previous application dummy is negative and significant, which ceteris paribus seems to imply that foreign entry is likely to deter firms with previous history of patent applications to apply again. This result is quite puzzling: Why firms with previous patent applications are more likely to be discouraged? A careful look into our results solves this puzzle. Our explanation is that firms with previous patent applications are not homogeneous either. In this group, there are firms with a fairly continuous pattern of patent applications over the years; there also exist firms with very sporadic filing records. The latter subgroup may file one or two applications in a certain year, but remain dormant for years at a time. It is this group that is most likely to have the continuity of their patenting activity disrupted by foreign entry. Based on the fact that around 90% of observations in our sample are zero, we believe the effect from the latter subgroup must dominate. And this is why overall we see a negative impact of foreign entry.

In the second stage of the hurdle/two-part model, we run a *zero-truncated* negative binomial count model after adjusting for error term from the first stage[20]. Foreign entry has a negative significant impact on patent applications in the second stage, which implies that higher foreign entry rates discourage firms from filing for more patent applications. This result is puzzling and needs further investigation. Our key interactive term between foreign entry and technological distance is positive but not significant. We reconcile this result with the first stage by the notation that the second-stage firms may have a lesser degree of heterogeneity in terms of their technological distance with foreign firms. After all, they all had filed for patent applications so they tend to be more technologically advanced..

One last interesting finding is the seemingly contradictory impact of firm size. In section 4.1 where our focus is on firm's labor productivity growth, the coefficient on firm size is negative. However, in section 4.2 and 4.3 where we investigate foreign entry's impact on firms' innovation behavior, we find a significantly positive coefficient on the same variable. Initially puzzling, this result in fact matches economic theory quite nicely.

[20] This two-part process was automatically done using the Stata command, HNBLOGIT, which stands for hurdle negative binomial logit model.

When firms grow bigger, it often coincides with the fact that they have entered a more mature stage of development, thus its productivity growth may not be as fast as before when they are smaller. However, when firms are big, it's likely that more employees engage in innovative activities, and more employees are also likely to come up with more creative ideas. So the relationship between firm size and innovation tends to be positive.

To summarize the above regression results, we find strong evidence that, like R&D intensity, foreign entry has a heterogeneous impact on domestic firms' patenting activities. In the ZINB model, firms closer to the technological frontier tend to file for more patent applications; firms that are technologically far behind tend to file fewer applications than they would in the absence of foreign entry. In the hurdle model, we find a similar pattern in firm behavior concerning whether to file for patent applications, but there is no evidence to support the hypothesis that foreign entry has a divergent effect on the number of patents applied.

5. Conclusion

In this paper we apply Schumpeter's idea of "creative destruction" in an international setting and use a large dataset of Chinese large and medium-size enterprises to test empirically whether foreign entry produces a divergent growth pattern among domestic incumbents. We find that in the face of foreign entry domestic firms with more advanced technologies choose head-to-head competition with their foreign competitors; these firms strategically invest in technological innovations to fend off the competition associated with foreign entry. For those lagging firms that have large technological gaps with their foreign peers, foreign entry has a significant "discouragement effect". It not only slows down the productivity growth of incumbents, but also discourages incumbents from engaging in innovation activities that improve their future growth potential. However, on the net, foreign entry still has a positive effect on the productivity growth of domestic firms.

Our research invites future work on new avenues of the impact of foreign entry. We show that there exists a much more complicated relationship between foreign and domestic firms than previously thought. Domestic firms do not simply receive the benefits from technology spillover passively, but they also respond strategically to foreign entry by adjusting their innovation behaviors. The interactions induced by foreign entry create an economic dynamism within the economy, and according to Edmund Phelps, it is essential for a country's long term development[21], "This dynamism that the economic model possesses is a crucial determinant of the country's economic performance: Where there is more entrepreneurial activity -- and thus more innovation, […] -- there are more jobs to fill, and those added jobs are relatively engaging and fulfilling. Participation rises accordingly and productivity climbs to a higher path".

[21] Source: Phelps, "Entrepreneurial Culture", *Wall Street Journal*, Feb. 12, 2007.

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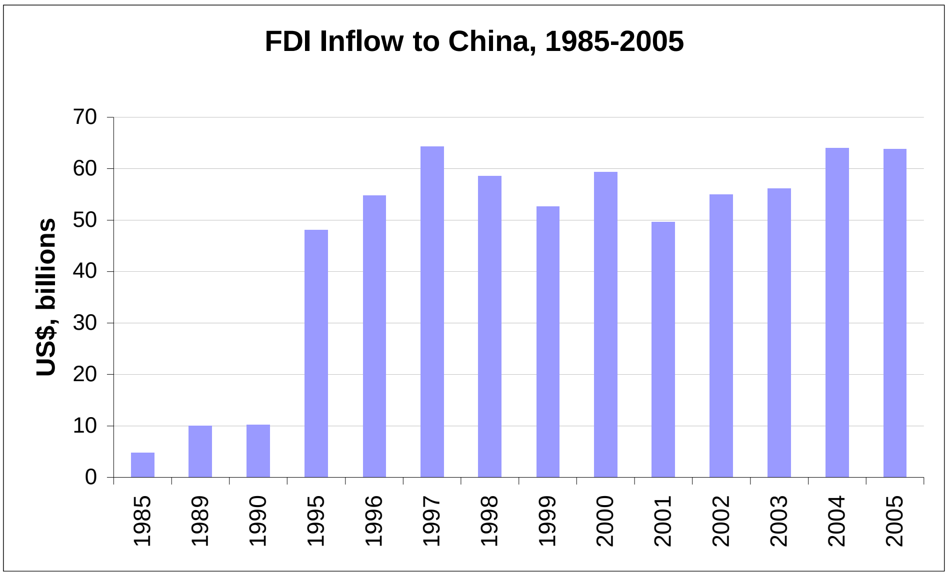
Figure 1: Foreign Direct Investment (FDI) to China, 1985-2005



Source: China Statistics Year Book 2006, China's National Bureau of Statistics

Figure 2

Average Foreign Entry Rate by 2-digit Chinese Manufacturing Industry, 1995-2004

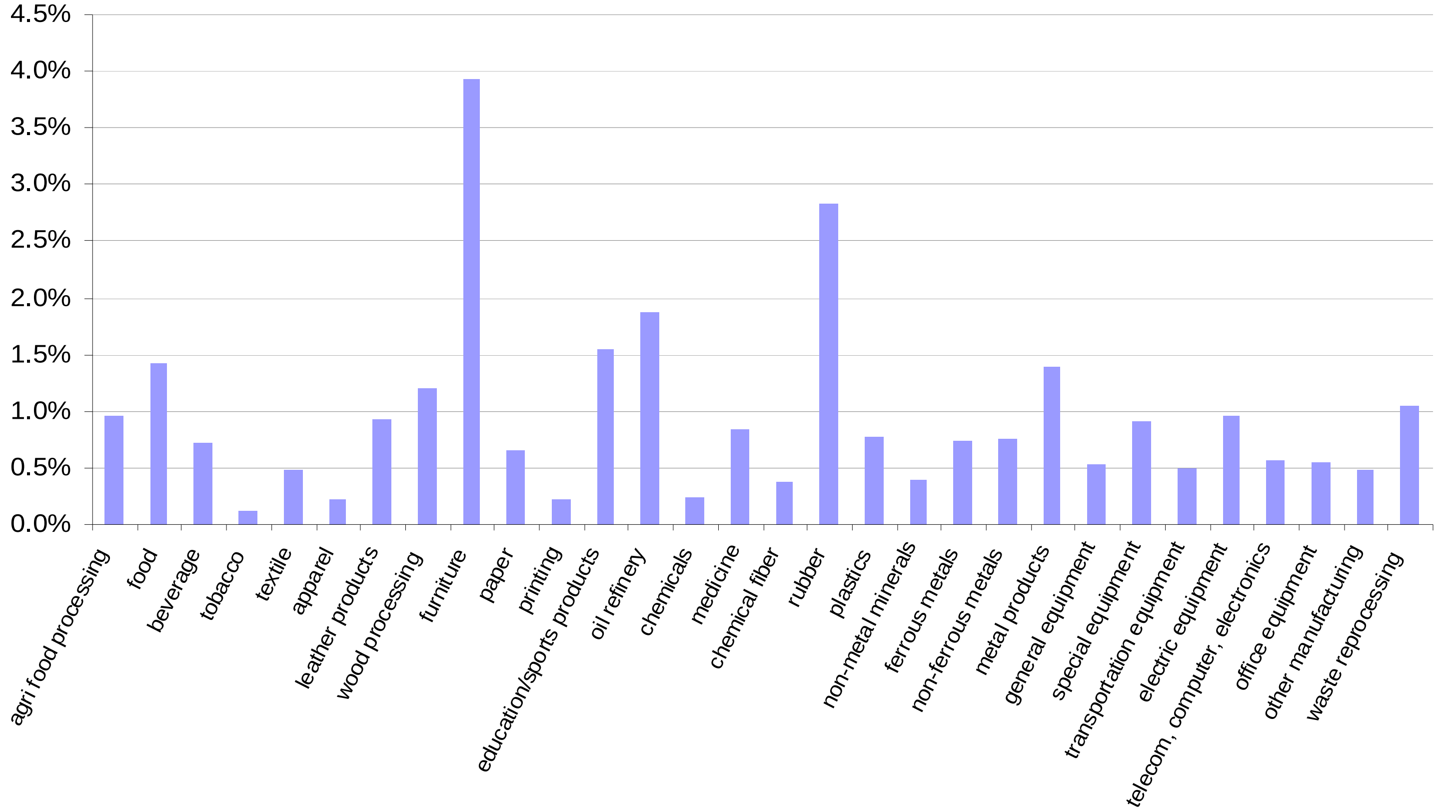
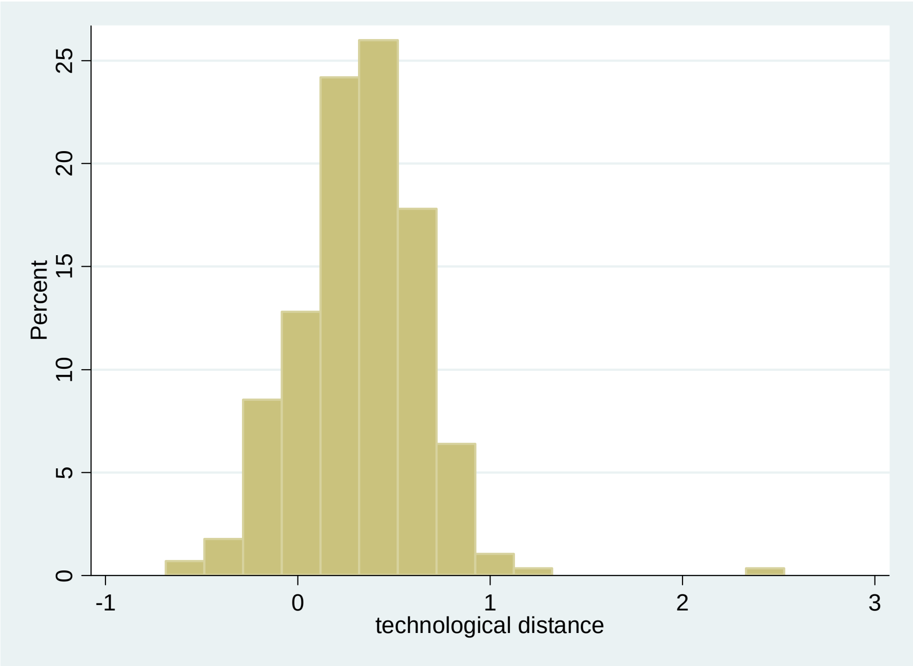


Figure 3 Histogram of Technological Distance (1995-2004)
percent (technological distance>0) = 85.8%



Note: tech. distance is measured by natural log of relative labor productivity between foreign firms and domestic firms at the 3-digit industry level (refer to equation (3) for details).

Figure 4-1 Foreign Entry and Productivity Growth

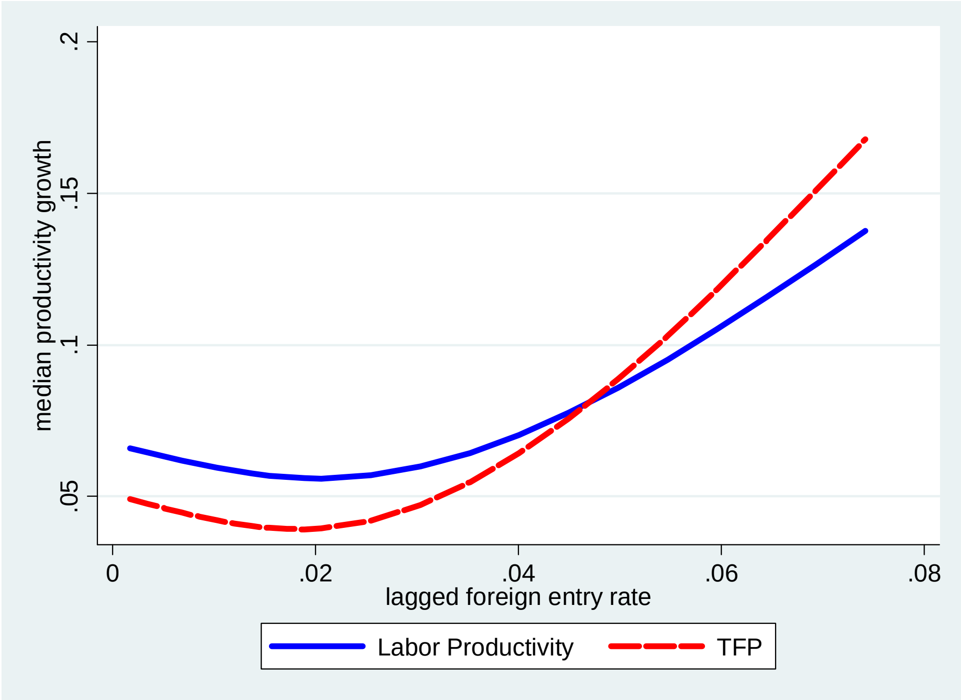
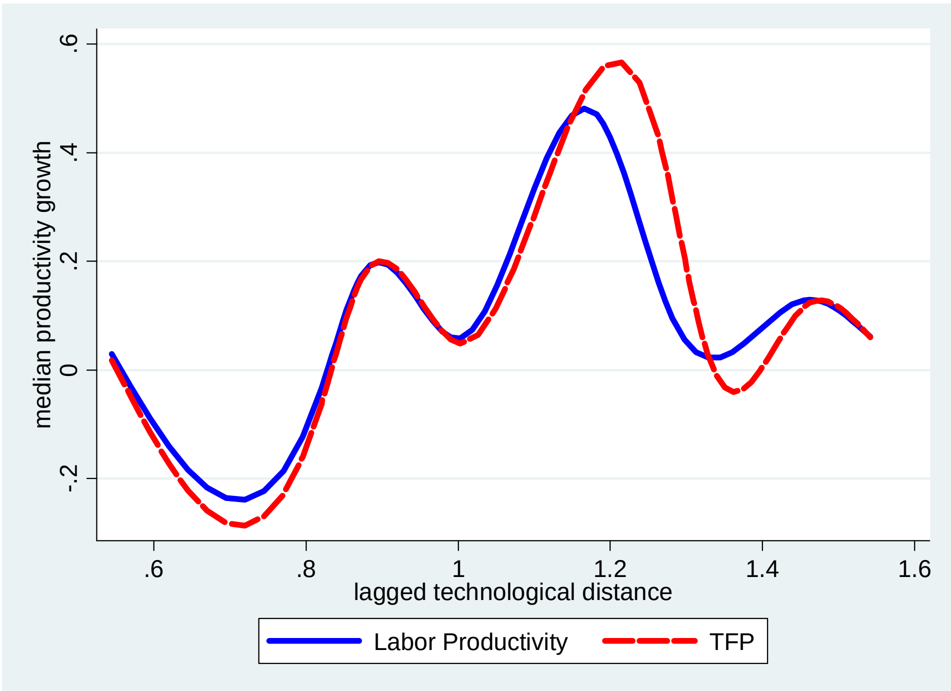


Figure 4-2 Technological Distance and Productivity Growth



Note: Figures 4-1 and 4-2 are plot in STATA using median spline curve. Foreign entry rates and tech. distance are divided into ten bands with each band containing the same number of observations. Productivity growth shown in the graph is the median growth of firms with the same entry rate.

Table 1 Share of Foreign Firms in China's Manufacturing Sectors 1995-2004

year	number of firms %		employment %		VA %		Sales %	
	foreign	foreign+JVs	foreign	foreign+JVs	foreign	foreign+JVs	foreign	foreign+JVs
1995	0.4%	9.9%	0.2%	4.1%	1.3%	11.7%	0.9%	13.2%
1996	1.0%	11.8%	0.4%	5.0%	1.3%	13.7%	1.8%	15.6%
1997	1.3%	12.6%	0.6%	5.3%	1.5%	14.6%	2.1%	16.3%
1998	2.5%	14.4%	1.7%	6.6%	3.9%	16.7%	4.9%	19.3%
1999	3.6%	17.0%	2.2%	7.7%	4.5%	18.6%	5.8%	21.6%
2000	4.4%	18.9%	3.0%	9.4%	5.6%	20.5%	5.8%	23.1%
2001	7.9%	24.6%	4.9%	12.4%	8.5%	24.6%	9.6%	28.1%
2002	9.5%	27.0%	6.3%	14.1%	10.1%	26.4%	11.3%	29.3%
2003	20.6%	43.0%	15.4%	28.5%	14.2%	33.5%	17.7%	38.4%
2004	29.7%	55.5%	23.8%	39.9%	19.2%	39.7%	24.9%	47.2%

Source: NBS and authors' own calculation based on China LME dataset.

Table 2 Foreign Entry by 3-digit Industries

rank	SIC3	industry description	entry rate	year
industries with the highest entry rate				
1	135	aquatic products	0.0698	1995
2	344	container manufacturing	0.0511	1995
3	268	chemical products	0.0276	1995
4	132	vegetable oil	0.0247	1995
5	152	soft drinks	0.0232	1995
1	221	paper pulp	0.1905	2004
2	211	wood furniture	0.0718	2004
3	391	electricity generation equipment	0.0638	2004
4	274	pharmaceuticals	0.0580	2004
5	403	TV broadcasting equipment	0.0572	2004
industries with the lowest entry rate				
1	261	basic chemicals	0.0002	1995
2	172	textile	0.0004	1995
3	411	telecom equipment	0.0005	1995
4	354	bearing manufacturing	0.0007	1995
5	131	cattle feeding products	0.0011	1995
1	322	steel making	0.0005	2004
2	411	general instrument	0.0016	2004
3	192	leather products	0.0018	2004
4	366	special electronics (military, astro, aeronautics)	0.0025	2004
5	231	printing	0.0026	2004

Table 3 Domestic industries' technological distance with foreign firms

Domestic Industries with largest technological distance

SIC3	3-digit industry description	tech. distance
368	medical instruments and equipment	0.757
361	mining, metallurgical and construction equipment	0.711
219	other furniture manufacturing	0.664
367	Agricultural etc. special equipment	0.636
335	non-ferrous metal processing	0.634
223	paper products	0.617
261	basic chemical materials	0.604
372	automobile	0.584
139	other agricultural food products	0.559
313	construction materials	0.555

Domestic Industries with smallest technological distance

SIC3	3-digit industry description	tech. distance
244	toys	-0.208
392	electricity transmission and controlling equipment	-0.218
134	sugar manufacturing	-0.243
431	metal waste processing	-0.273
181	apparel	-0.294
176	textile	-0.333
406	electronic unit device	-0.348
192	leather products	-0.351
395	home electronics	-0.524
323	steel making	-0.688

note: technological distance is measured by labor productivity gap between foreign firms (including JVs) and domestic firms.

Table 4 Percentage of firms with innovation activities

year	total firms	R&D expenditure>0, %		patent application>0, %	
		domestic	foreign+JVs	domestic	foreign+JVs
1995	5950	17.4%	1.6%	4.8%	0.5%
1996	10890	23.1%	2.8%	5.5%	0.6%
1997	13021	24.0%	3.2%	4.6%	0.6%
1998	14985	24.8%	3.5%	5.2%	0.8%
1999	16406	25.5%	4.2%	5.7%	0.9%
2000	16046	27.1%	4.5%	6.9%	1.4%
2001	16941	24.1%	5.9%	7.3%	1.8%
2002	16720	24.9%	7.2%	7.9%	2.0%
2003	13538	22.9%	9.2%	9.1%	3.6%
2004	14628	16.4%	9.5%	8.3%	4.7%

Table 5 Descriptive statistics

	Mean	Std. dev	Min	Max
Labor productivity, LP (VA/L)*	49.12	74.06	0.35	753.66
Growth of labor productivity	0.057	0.634	-6.741	5.410
Total Factor Productivity, TFP*	7.68	25.12	0.00	1412.99
Growth of TFP	0.030	0.708	-6.800	5.430
R&D intensity, log(R&D/VA)	0.02	0.09	0.00	3.58
Patent applications	0.7	8.1	0.0	622.0
Foreign entry rate	0.0062	0.0130	0.0000	0.1905
Technological distance (3-year average)	1.03	0.40	-0.21	1.91
Capital/labor ratio (K/L)*	93.30	170.20	0.60	5404.40
firm size (measured by total employed labor)	1315	2740	66	117489
Industry concentration ratio (Top 3 firms)	0.20	0.12	0.04	0.70

Notes: * The unit of measurement for labor productivity and capital labor ratio ¥1000 per capita.

*TFP here is calculated as such that the input-output elasticity (a, b) are estimated allowing firms in different industries (2-digit) to have different production functions. Firms within the same industry are assumed to have the same production function.

Table 6a: Productivity growth models

	Dependent variable: gLP, growth of labor productivity			
	Pooled OLS		OLS w/ Fixed Effects	
Independent variables:	(1)	(2)	(3)	(4)
foreign entry (%), (t-1)	0.042	0.177	0.239*	1.143***
	(0.098)	(0.122)	(0.136)	(0.313)
technological distance, (t-1)	0.131***	0.232***	0.893***	1.680***
	(0.039)	(0.064)	(0.350)	(0.432)
entry(t-1) * distance (t-1)	-0.083	**-0.162****	-0.133	**-0.522*****
	(0.074)	(0.085)	(0.098)	(0.155)
growth of capital-labor ratio (t)	0.218***	0.215***	0.202***	0.141***
	(0.020)	(0.020)	(0.024)	(0.025)
firm scale L (t)		-0.008		-0.390***
		(0.009)		(0.051)
industry concentration (t-1)		-0.042**		-0.666***
		(0.021)		(0.213)
constant	-0.091**	-0.247**	-0.914***	-0.578
	(0.047)	(0.120)	(0.349)	(0.908)
year dummies	No	No	Yes	Yes
firm fixed effects	No	No	Yes	Yes
number of obs	4,508	4,508	4,508	4,508

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

Table 6b: Productivity growth models: LP and TFP

Independent variables:	Dependent variable: gLP* (1)	gTFP1* (2)	gTFP2* (3)
foreign entry (%), (t-1)	1.143***	1.284***	1.243***
	(0.313)	(0.346)	(0.348)
technological distance, (t-1)	1.680***	1.863***	1.793***
	(0.432)	(0.478)	(0.481)
entry(t-1) * distance (t-1)	**-0.522*** **	**-0.600*** **	**-0.578*** **
	(0.155)	(0.172)	(0.173)
growth of capital-labor ratio (t)	0.141***		
	(0.025)		
firm scale L (t)	-0.390***	-0.370***	-0.371***
	(0.051)	(0.054)	(0.054)
industry concentration (t-1)	-0.666***	-0.726***	-0.696***
	(0.213)	(0.235)	(0.237)
constant	-0.578	-1.049	-0.907
	(0.908)	(0.996)	(1.002)
year dummies	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes
number of obs	4,508	4,508	4,505

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

*gLP: growth of labor productivity;

*gTFP1: growth of TFP1. TFP1 is calculated using TFP=(VA/K)^a x (VA/L)^b, where a=0.23 and b=0.77 and they are regression estimates assuming all firms have the same production function.

*gTFP2: growth of TFP2. The difference from TFP1 is input-output elasticity (a, b) are estimated allowing firms in different industries (2-digit) to have different production functions, but firms within the same industry have the same production function.

Table 6c: Productivity growth models, with categorical distance dummies in interactive terms

	Dependent variable:					
	Labor Productivity Growth			TFP Growth*		
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)
foreign entry rate (%), (t-1)	1.143***	0.821***	0.319***	1.243***	0.868***	0.326***
	(0.313)	(0.263)	(0.110)	(0.348)	(0.292)	(0.123)
technological distance, (t-1)	1.680***	1.239***	1.239***	1.793***	1.291***	1.291***
	(0.432)	(0.374)	(0.374)	(0.481)	(0.416)	(0.416)
entry(t-1) * distance(t-1)	**-0.522*** **			**-0.578*** **		
	(0.155)			(0.173)		
entry(t-1) * D_fardist (t-1)		**-0.501*** **			**-0.542*** **	
		(0.180)			(0.201)	
entry(t-1) * D_neardist(t-1)			**0.501*** **			**0.542*** **
			(0.180)			(0.201)
growth of capital-labor ratio (t)	0.141***	0.141***	0.141***			
	(0.025)	(0.025)	(0.025)			
firm scale L (t)	-0.390***	-0.390***	-0.390***	-0.371***	-0.372***	-0.372***
	(0.051)	(0.051)	(0.051)	(0.054)	0.054	0.054
industry concentration (t-1)	-0.666***	-0.544***	-0.544***	-0.696***	-0.550***	-0.550***
	(0.213)	(0.206)	(0.206)	(0.237)	(0.229)	(0.229)
constant	-0.578	0.160	0.160	-0.907	-0.047	-0.047
	(0.908)	(0.820)	(0.820)	(1.002)	(0.903)	(0.903)
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
number of obs	4,508	4,508	4,508	4,505	4,505	4,505

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

*TFP growth: TFP here is calculated as such that the input-output elasticity (a, b) are estimated allowing firms in different 2-digit industries to have different production functions. Firms in the same industry are assumed to have the same production function.

*categorical distance dummies are created in the following manner: first calculate median distance for technological distance in year t, then D_near_distance=1 if technological distance < median value; D_far_distance=1 if distance >= median value.

Table 6d: Productivity growth models with Heckman 2-step correction of selection bias

	Dependent variable:			
	LP growth		TFP growth*	
	without correction	Heckman correction	without correction	Heckman correction
Independent variables:	(1)	(2)	(3)	(4)
foreign entry (%), (t-1)	1.143***	1.125***	1.243***	1.311***
	(0.313)	(0.451)	(0.348)	(0.501)
technological distance, (t-1)	1.680***	1.628**	1.793***	1.913**
	(0.432)	(0.781)	(0.481)	(0.870)
entry(t-1) * distance (t-1)	**-0.522*****	**-0.544*****	**-0.578*****	**-0.633*****
	(0.155)	(0.214)	(0.173)	(0.238)
growth of capital-labor ratio (t)	0.141***	0.138***		
	(0.025)	(0.025)		
firm scale L (t)	-0.390	-0.414***	-0.371	-0.392***
	(0.051)	(0.052)	(0.054)	(0.055)
industry concentration (t-1)	-0.666***	-0.588**	-0.696***	-0.658**
	(0.213)	(0.299)	(0.237)	(0.333)
constant	-0.578	-0.229	-0.907	-0.904
	(0.908)	(1.431)	(1.002)	(1.589)
year dummies	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes
number of obs	4,508	4,508	4,505	4,505

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

*TFP growth: TFP here is calculated as such that the input-output elasticity (a, b) are estimated allowing firms in different 2-digit industries to have different production functions. Firms in the same industry are assumed to have the same production function.

Table 6e: Productivity growth models with endogeneity

	Dependent variable					
	gLP (growth of labor productivity)			gTFP (growth of total factor productivity)*		
	Fixed Effects OLS	Arellano-Bond GMM	Blundell-Bond GMM	Fixed Effects OLS	Arellano-Bond GMM	Blundell-Bond GMM
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)
foreign entry (%), (t-1)	1.143***	1.089***	0.377***	1.243***	1.200***	0.432***
	(0.313)	(0.341)	(0.130)	(0.348)	(0.376)	(0.144)
technological distance, (t-1)	1.680***	1.528***	0.362***	1.793***	1.655***	0.391***
	(0.432)	(0.421)	(0.067)	(0.481)	(0.476)	(0.074)
entry(t-1) * distance (t-1)	**-0.522*** **	**-0.498*** **	**-0.216*** **	**-0.578*** **	**-0.561*** **	**-0.258*** **
	(0.155)	(0.167)	(0.092)	(0.173)	(0.184)	(0.102)
growth of capital-labor ratio (t)	0.141***	0.090**	0.202***			
	(0.025)	(0.045)	(0.043)			
firm scale L (t)	-0.390***	-0.651***	-0.033***	-0.371***	-0.571***	-0.033***
	(0.051)	(0.096)	(0.011)	(0.054)	(0.093)	(0.012)
industry concentration (t-1)	-0.666***	-0.615***	-0.118***	-0.696***	-0.647***	-0.121***
	(0.213)	(0.244)	(0.022)	(0.237)	(0.271)	(0.025)
constant	-0.578		-0.440***	-0.907		-0.502***
	(0.908)		(0.134)	(1.002)		(0.147)
Arellano-Bond AR2 test		(0.115)	(0.111)		(0.041)	(0.046)
Hansen J test		(0.463)	(0.031)		(0.305)	(0.027)
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
number of obs	4,508	2,819	4,508	4,505	2,817	4,505

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

*gTFP: growth of TFP. TFP here is calculated as such that the input-output elasticity (a, b) are estimated allowing firms in different industries (2-digit) to have the different production functions. Firms within the same industry are assumed to have the same production function.

Table 6f: Productivity growth models with stricter heterogeneity at firm level

Independent variables:	Dependent variable: gLP* (1)	gTFP1* (2)	gTFP2* (3)
foreign entry (%), (t-1)	0.299***	0.305**	0.294**
	(0.125)	(0.138)	(0.139)
technological distance, (t-1)	0.840***	0.913***	0.914***
	(0.040)	(0.044)	(0.045)
entry(t-1) * distance (t-1)	**-0.074***	**-0.081***	-0.074
	(0.043)	(0.048)	(0.048)
growth of capital-labor ratio (t)	0.124***		
	(0.023)		
firm scale L (t)	-0.343***	-0.305***	-0.302***
	(0.047)	(0.050)	(0.050)
industry concentration (t-1)	-0.164	-0.146	-0.137
	(0.129)	(0.143)	(0.144)
constant	0.678	0.339	0.221
	(0.463)	(0.502)	(0.524)
year dummies	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes
number of obs	4,582	4,582	4,582

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

*gLP: growth of labor productivity;

*gTFP1: growth of TFP1. TFP1 is calculated using TFP=(VA/K)^a x (VA/L)^b, where a=0.23 and b=0.77 and they are regression estimates assuming all firms have the same production function.

*gTFP2: growth of TFP2. The difference from TFP1 is input-output elasticity (a, b) are estimated allowing firms in different industries (2-digit) to have different production functions, but firms within the same industry have the same production function.

Table 7 Regression models on R&D intensity

Independent variables:	Dependent variable: R&D Intensity, ln(R&D/VA)					
	OLS		**Tobit**		**Random-effects Tobit**	
	(1)	(2)	(3)	(4)	(5)	(6)
foreign entry, (t-1)	0.023**	-0.005	0.104***	0.125***	0.063**	0.070**
	(0.012)	(0.016)	(0.030)	(0.031)	(0.030)	(0.031)
technological distance, (t-1)	0.031***	-0.029	0.106***	0.109***	0.095***	0.088***
	(0.005)	(0.042)	(0.012)	(0.012)	(0.013)	(0.014)
entry(t-1) * distance(t-1)	**-0.017****	0.002	**-0.074*****	**-0.086*****	**-0.047****	**-0.036***
	(0.009)	(0.012)	(0.022)	(0.023)	(0.022)	(0.023)
capital-labor ratio, K/L		-0.001		0.023***		0.021***
		0.004		0.003		0.004
firm scale, L		-0.001		0.027***		0.029***
		0.007		(0.002)		(0.003)
constant	-0.017***	0.063	-0.196***	-0.482***	-0.192***	-0.498***
	(0.006)	(0.070)	(0.015)	(0.029)	(0.016)	(0.039)
year dummies	No	Yes	No	No	No	Yes
firm fixed/random effects	No	Yes	No	No	Yes	Yes
number of observations	4,512	4,512	4,512	4,512	4,512	4,512

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

Table 8 Negative binomial (NB) count models on patent applications

Independent variables:	Dependent variable: patent applications							
	(1)	(2)	(3)	(4)	(5)		(6)	
	model name							
	NB*	NB	XTNB*	XTNB	Zero-Inflated (ZINB)		Hurdle/Two-part	
			random effects	random effects	zero-inflate (ptapp=0)	ptapp>0	logit (ptapp>0)	ZTNB* (ptapp>0)
foreign entry (%), (t-1)	2.849***	1.676*	1.576**	1.327*		1.115	2.028**	-3.095**
	(1.134)	(1.025)	(0.854)	(0.800)		(1.126)	(0.893)	(1.679)
technological distance, (t-1)	2.147***	1.179***	1.416***	0.907***		1.307***	1.099***	-1.022**
	(0.389)	(0.362)	(0.365)	(0.308)		(0.387)	(0.327)	(0.582)
entry(t-1) * distance(t-1)	**-2.387*** **	**-1.481** **	**-1.225** **	**-0.867**		**-1.296* **	**-1.096* **	1.219
	(0.862)	(0.781)	(0.592)	(0.565)		(0.817)	(0.626)	(1.141)
capital-labor ratio, K/L		0.893***		0.314***			0.338***	0.388
		(0.117)		(0.085)			(0.089)	(0.150)
firm scale, L		0.793***		0.249***			0.326***	0.352***
		(0.094)		(0.058)			(0.067)	(0.116)
stock of previous patent applications				0.003*	-0.535***		-0.001	0.022
				(0.002)	(0.148)		(0.008)	(0.015)
D(previous app>0)				2.264***	-1.575***		2.607***	0.328
				(0.139)	(0.319)		(0.200)	(0.382)
foreign entry (t-1) *stock of ptapp							**0.084** **	-0.002
							(0.043)	(0.046)
foreign entry(t-1)*D(previous app>0)							**-0.957** **	0.748
							(0.465)	(0.903)
constant	-3.283***	-11.782***	-2.867***	-7.534***	2.677***	-0.253	-8.513***	-2.920**
	(0.485)	(0.880)	(0.482)	(0.685)	(0.123)	(0.520)	(0.751)	(1.293)
number of obs	4,512	4,512	4,512	4,512	4,512		4512 (with 4181 zero patent application obs)	

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level.

NB: negative binomial model; XTNB: NB with random effects; ZINB: zero-inflated negative binomial model; ZTNB: Zero-truncated negative binomial model.