

Foreign Entry and Heterogeneous Growth of Firms: Do We Observe “Creative Destruction” in China?

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Abstract

We adopt the framework of Schumpeterian creative destruction formalized by Aghion et al. (2006) to analyze the impact of foreign direct investment on domestic firms. In the face of foreign entry, domestic firms may exhibit heterogeneous patterns of growth depending on their technological distance from foreign firms. Domestic firms in industries that are closer to the foreign technology frontier may choose to compete, while firms in industries that are further down on the technology ladder may suffer a “discouragement effect” and lag further behind. We test the hypothesis using firm-level data of China’s Large and Medium-Size Enterprise (LME). We find that foreign entry indeed generates a heterogeneous impact on the productivity growth of Chinese domestic incumbents. This finding has important policy implications to the debate on FDI and its impact on domestic firms.

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1. Introduction

The impact of foreign direct investment (FDI) on domestic firms is often thought to be homogeneous, at least as so modeled. On the positive side, theories predict that domestic firms will benefit from the interactions with foreign firms and receive positive spillover effect. On the negative side, 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 To a large extent, the debate so far failed to take firm heterogeneity into consideration. Inspired by the earlier work of Aghion et al. (2005b, 2005c, 2006), we show in this paper that the impact of FDI on domestic firms is far more complicated than previously thought. Depending on the technological distance between domestic and foreign firms, FDI can have a divergent or heterogeneous impact on domestic firms.

Our research is ultimately 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 firm's diverse nature, including the notion that firms compete for survival in a fashion similar to Darwinism. National economy moves ahead through the *dynamism* generated by the so-called creative destruction, where more productive firms (often newer ones) constantly replace less productive (often older) ones. Aghion and Howitt (1992) constructed a formal model of innovation to capture the essence of this process. In Aghion and Howitt (1998), they

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".

refined their early argument by pointing out that it is too simple to assume incumbents will automatically be replaced; facing new competition, incumbents will fight for survival; and whether incumbents will survive depends on the outcome of the competition. As such, new entrants' impact on incumbents tends to be heterogeneous, and an important source of such heterogeneity is firm's initial productivity level relative to the new competitors. Aghion et al. (2006) empirically tested a version of the idea using UK data, and the results seemed to confirm their hypothesis.

Our research is another attempt to apply such framework to the real world. Like Aghion et al. (2006), we are especially interested in finding out how foreign entry could potentially change the growth dynamics of domestic firms. We define the heterogeneity of domestic firms in 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.

The contribution of this research is to apply firm heterogeneity and the new insights from Schumpeterian "creative destruction" to the debate of an important policy question, i.e., the impact of FDI on domestic firms. Empirical studies on the impact of FDI, especially those on developing economies, yielded 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." It won't take a genius to figure out a scenario where the positive spillover effect can be partially or fully offset by the so-called "market-stealing" effect (see for example, Aitken and Harrison, 2002). This is plausible especially when there exists a large technological gap between firms in developed countries and that in developing countries. Because the impact of FDI could go both ways, it is not surprising that past empirical research tended to find mixed (if not confusing) results. On the 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; On the other hand, the analysis of Haddad and Harrison (1993) on Morocco, Aitken and Harrison (1999) on Venezuela, Djankov and Hoekman (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 the heterogeneity of domestic firms. And domestic firms were uniformly treated as a homogeneous group. Such homogeneous treatment of domestic firms directly contributed to the confusing results in FDI literature.

We argue in this paper that the analysis of the impact of FDI should take a new direction by taking firm heterogeneity into account. In our view, this new approach captures the dynamics between foreign and domestic firms more richly and more accurately, and offers a potential solution to the empirical puzzle outlined above.

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 inflows into China from 1982 to 2009. China's FDI boom started around 1993, and FDI inflows have hovered around US \$40-50 billion per year during our sample period, 1995-2004. Second, China's growth in the past 30 years has been nothing short of being spectacular. It can be argued that this growth was, to a large extent, due to China's re-opening up to the rest of the world, especially its remarkable openness to foreign direct investment. To put things into perspective, by growing at a rate of 9% per year, China essentially doubles the living standards of its people in roughly every 8 years. This is one of the greatest achievements in the economic development of human history. As such, understanding the internal dynamics of this large open economy is of particular interest to many people, including economists and policy makers.

[Figure 1 here]

Here is a preview our empirical results. We find strong evidence that foreign entry increases the productivity growth of Chinese domestic firms on average, but the growth of individual domestic incumbents depends on their technological position relative to foreign competitors. For domestic firms in the industries that are closer

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

(farther) to technology frontier, a 1% increase of foreign entry leads to roughly 0.6% *additional* increase (decrease) of TFP growth.

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 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.

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:

$$\begin{aligned} \Delta LP_{ijt} = & \alpha + \beta_1 FE_{jt-1} + \beta_2 Dist_{jt-1} + \beta_3 FE_{jt-1} * Dist_{jt-1} + \beta_4 \Delta KL_{ijt} + X'_{ijt-1} \gamma \\ & + u_i + \delta_j + \tau_t + \varepsilon_{ijt}, \end{aligned} \quad (1)$$

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 productivity³ at firm level, $LP_{ijt} = (VA/L)_{ijt}$, where VA denotes value-added, and L denotes labor

employment. Growth of labor productivity is simply defined as $\Delta LP_{ijt} = \ln\left(\frac{LP_{ijt}}{LP_{ijt-1}}\right)$. On

the right hand side of equation (1), FE represents foreign entry rate, $Dist_j$ measures technological distance between foreign and domestic firms in the same industry, j . Both variables use 3-year moving average to smooth out short-term volatility. Then FE_{jt-1} and

³ We also test the heterogeneity hypothesis using the growth of capital productivity and TFP as dependent variables later on.

$Dist_{jt-1}$ are one-period lag of the 3-year moving average. The 3-year moving average enables us to capture foreign entry's impact on productivity growth with deeper lags. This is quite important, as the impact of new foreign direct investment may not show up contemporaneously. Our lag structure enables us to capture the effect of foreign entry on domestic firms in a longer period. To capture the heterogeneous effect of foreign entry on domestic firms, like Aghion et al (2006), we also include an interaction term between foreign entry rate and relative 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.

We also control of growth of capital-labor ratio since labor productivity growth may be due to increase of capital intensity. Note that although our dependent variable is a measure of labor productivity growth, after controlling for growth of capital-labor ratio, we are essentially estimating an equation of TFP growth. In equation (1), X is a vector of control variables. These include firm size as measured by the firm's total employment to control for scale, and the industry concentration ratio⁴ to capture industry-level competition.⁵ The error term is structured to include u_i to control for firm-level fixed effects, δ_j to control for industry-specific effects, and year dummy τ_t to control for time-effects.

We measure the foreign entry rate using the following formula:

$$FE_{jt} = (e_{jt} + e_{jt-1} + e_{jt-2}) / 3,$$

$$\text{and } e_{jt} = \frac{\sum_{i=1}^{N_{jt}} L_{it} * D_{ijt} (Foreign \& JV, new_entry)}{\sum_{i=1}^{N_{jt}} L_{it}}, \quad (2)$$

⁴ We measure industry concentration ratio (CR) by the share of sales of the top three firms in industry j:

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

⁵ Both firm size and the industry concentration ratio are logarithm values.

where N_{jt} is the total number of firms in the 3-digit industry j in year t . D_{ijt} is a dummy, which assumes the value of one if a foreign firm (including joint ventures) *newly* enters⁶ industry j at time t , and zero otherwise. In words, foreign entry is a 3-year moving average of yearly entry rate e_{jt} , where e_{jt} is the ratio of labor employment of newly entered foreign firms relative to the total labor employment in the same industry j and year t . Technological distance is measured by the ratio of labor productivity between foreign firms and domestic firms in the same industry j :

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

where F and D denotes foreign and domestic, respectively. Foreign firms here include both foreign owned and joint ventures between foreign and domestic firms. To mitigate potential measurement error, again 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 be either positive or negative. For technological distance, we expect to see a strong positive coefficient as the advantages of backwardness suggests that firms with initial 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.

⁶ To identify new entry, in our data, we match firms' recorded opening year with their observation year t .

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. In 2004, they accounted 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 FDIs and have had big influence on various metrics, we chose to 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. To get an overall picture of foreign entry rate, 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 technological distance between newly entered foreign firms and domestic firm should be greater than zero. 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. To verify whether our assumption is true, we plot a histogram of technological distance in Figure 3. From the histogram, we find that majority of distance values are indeed greater than zero. In over 85% of industries, on average, new foreign firms have relatively higher labor productivity than domestic firms.

[Figure 3 here]

In the rest 15% 3-digit industries, foreign entrants, on average, have lower productivity than domestic firms. This makes a lot of sense as one can not always assume all foreign firms entering into Chinese market enjoy more advanced technology. Some were attracted by the cheap labor in China, while others were attracted by special tax treatment to foreign invested firms.⁷ In Table 2, we list top 5 industries with the highest and lowest technological gap during the whole sample period, 1995-2004. Industries in which foreign firms have the highest technology lead include chemicals, medical instruments, and general equipment. In contrast, Chinese domestic industries enjoy relative advantage in manufacturing of home electronics, sugar, metal and wood products.

[Table 2 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

⁷ 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.

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.⁸ 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]

4. Empirical Results and Discussions

Table 3 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, which is similar to what we showed in Figure 3.

[Table 3 here]

⁸ 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.

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 4. 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 4 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 firm fixed effects 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. (2006) 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.⁹

[Table 5a 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 4, we control for this problem by including capital intensity as the control variable.why TFP? In Table 5a, we test two variations of our baseline model by replacing growth of labor productivity with two measures of total factor productivity (TFP). The TFP estimates use a two-stage approach in which we first 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 5a. 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:

⁹ 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.

$$\ln(VA/L)_{ijt} = a_0 + \alpha \ln(K/L)_{ijt} + u_i + \tau_t + \varepsilon_{ijt}. \quad (4)$$

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, $\alpha=0.23$, so labor output elasticity, $\beta=1-0.23=0.77$. 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 (4) 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).¹⁰ So how to interpret these results? We use column (3) as an example to explain our findings. The coefficient of foreign entry, 0.496, indicates that a 1% increase of foreign entry in previous year correlates with roughly 0.5% 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 1.16% faster. The most interesting result is the coefficient on the interactive term. The coefficient, -0.470, indicates that with a 1% increase of foreign entry rate, domestic firms that are in industries that are closer to the foreign technological frontier tend to enjoy 0.47% additional TFP growth on average; while domestic firms in industries that are farther from the foreign technological frontier tend to suffer a negative TFP growth of 0.47% on average. In other words, foreign entry

¹⁰ 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.

has a heterogeneous effect on domestic firms productivity growth depending on the technological gap between domestic firms and foreign firms. Also remember, the heterogeneous effect captured by the interactive term is in addition to the effect independently captured by foreign entry.

Summarizing results tables 4 and 5a, 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, on average, roughly 22% of firms dropped out each year. 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 estimations. To deal with this potential problem, we follow the estimation method outlined in Wooldridge (2002), which is similar to the Heckman two-step

selection procedure. The difference is that it extends Heckman's method to the panel data setting and selection bias may appear each year sequentially.

We first run a probit model for each period: $s_{i,t+1} = \mathbb{I}[w_{it}\delta_t + v_{it} > 0]$, 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:

$$y_{it} = x_{it}\beta + \rho_2 d2_t \hat{\lambda}_{it} + \dots + \rho_T dT_t \hat{\lambda}_{it} + u_i + \delta_j + \tau_t + \varepsilon_{ijt}, \quad t \geq 2. \quad (5)$$

Here x_{it} includes foreign entry, technological distance, their interactive term and all other control variables as in equation (1). u_i, δ_j, τ_t again are firm-level fixed effects, industry dummies and time effects. To deal with selection bias from multiple periods, equation (5) 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 5b. Compared to the previous regression results in column (1) and (3), we find that our major regression variables still remain statistically significant and their signs unchanged. The interactive term, in particular, still remains negative and statistically significant. However, the magnitude of the negative coefficient becomes a little bigger (-0.513 vs. -0.414 for labor productivity growth; -0.594 vs. -0.470 for TFP growth). We think this makes perfect sense: If these domestic dropouts were to stay in our sample, we would have more firms with larger productivity gap with foreign firms. As such, foreign entry should have a more negative effect on the productivity growth of domestic firms.

[Table 5b 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 5c. 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.¹¹

[Table 5c 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 (0.111) and Hansen J-test statistic (0.218) 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 (0.117) is satisfying but IVs are suspected to be not orthogonal to the error term (0.008).

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

¹¹ 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.

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 (0.039) and we chose to mitigate the problem by using deeper lags in our estimation.

4.2.3. Stricter Heterogeneity

Finally, in Table 5d, we present another set of regression results based on an alternative measurement on technological distance. Instead of using the definition in equation (3),¹² we use the following formula to measure the technological gap:

$$Dist_{ijt} = \frac{1}{3} \sum_{z=0}^2 \ln \left(\frac{VA_{jt-z}^F / L_{jt-z}^F}{VA_{ijt-z}^D / L_{ijt-z}^D} \right), \quad (6)$$

The difference between equation (6) and equation (3) is that labor productivity of domestic firms in equation (6) is indexed at firm level, *i*, rather than on the industry level, *j*. This setup is a stricter measurement of technological distance, and it is quite intuitive. Now the technological distance becomes the difference between foreign entrants' average productivity and *individual* domestic firm's productivity.

The results of our initial round of regressions are presented in column (1) and (3) in Table 5d. Compared to previous estimation, we find that the coefficient on foreign entry becomes statistically insignificant albeit the sign is still positive; and the coefficient on technological distance still remains highly significant. Important to note, the coefficient of the interactive term between foreign entry and technological distance remains negative but no longer statistically significant. Lastly, the coefficient on the firm scale is highly significant but the coefficient on industry concentration becomes statistically insignificant. Overall, the results are less satisfactory when using firm-level measure of technological gap.

[Table 5d here]

We also experimented with some alternate specification on our estimation. We find that if we drop the variable, firm size, then the interactive term again becomes

¹² Aghion et al. (2006) uses the same definition, i.e., technological distance is indexed at industry level.

statistically significant and the sign of the coefficient as expected. These results are reported in column (2) and (4) of Table 5d. We can see that the coefficient of foreign entry still remains insignificant, however, the coefficient of the interactive term now become statistically significant at 5% level.

Our alternative measure of firm heterogeneity offers us some very interesting insights. Previously, we have confirmed that, in the face of 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 5d, we have further confirmed that the heterogeneous effect also exists among firms *within* the same industry, albeit the effect is less robust.

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 in technologically more advanced industries enjoy much faster productivity growth than the firms that are in technologically more backward industries.

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. The interactions induced by foreign entry create a much needed economic dynamism within the economy, and according to Edmund Phelps, it is essential for a country's long term development,¹³ "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".

¹³ Source: Phelps, "Entrepreneurial Culture", *Wall Street Journal*, Feb. 12, 2007.

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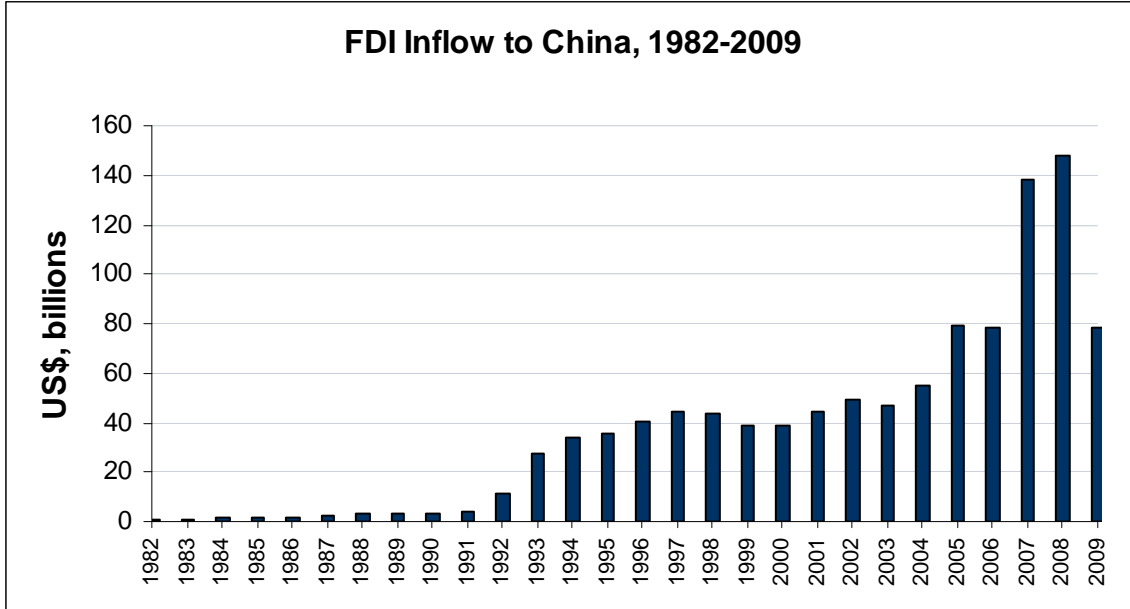
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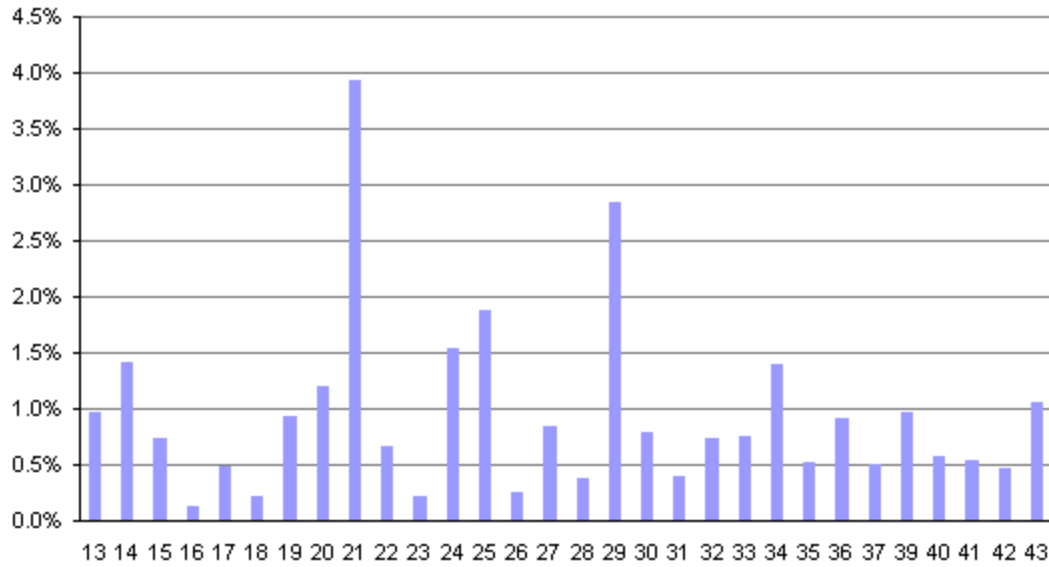
Figure 1: Foreign Direct Investment (FDI) to China, 1982-2009



Source: China's National Bureau of Statistics

Figure 2

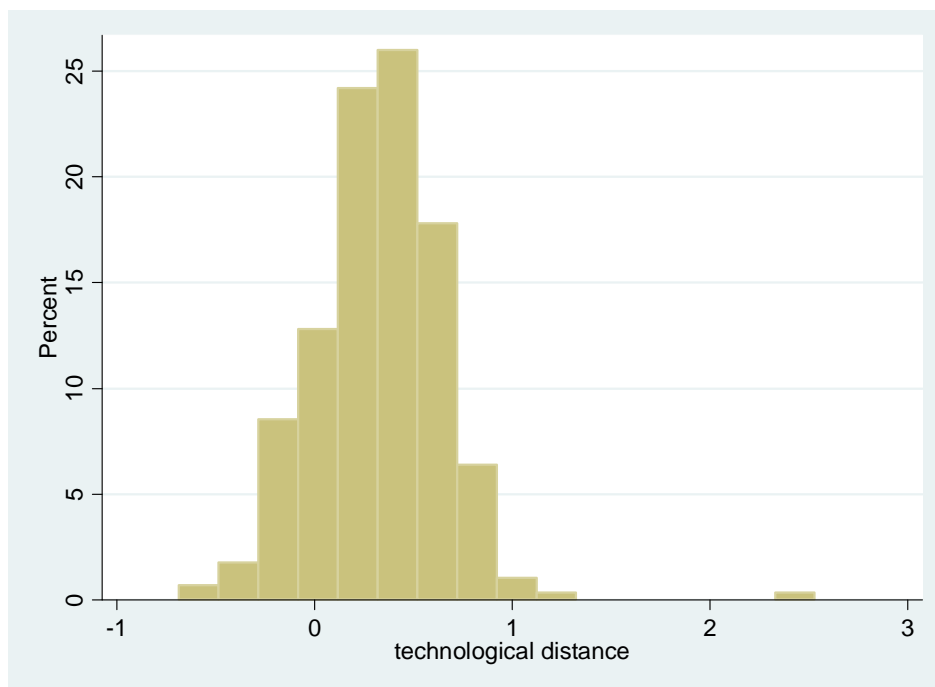
Foreign Entry Rate by 2-digit Chinese Manufacturing Industry, 10-Year Average (1995-2004)



SIC-2	Industry Description	SIC-2	Industry Description
13	agri food processing	28	chemical fiber
14	food	29	rubber
15	beverage	30	plastics
16	tobacco	31	non-metal minerals
17	textile	32	ferrous metals
18	apparel	33	non-ferrous metals
19	leather products	34	metal products
20	wood processing	35	general equipment
21	furniture	36	special equipment
22	paper	37	transportation equipment
23	printing	39	electric equipment
24	education/sports products	40	telecom, computer, electronics
25	oil refinery	41	office equipment
26	chemicals	42	other manufacturing
27	medicine	43	waste reprocessing

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

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

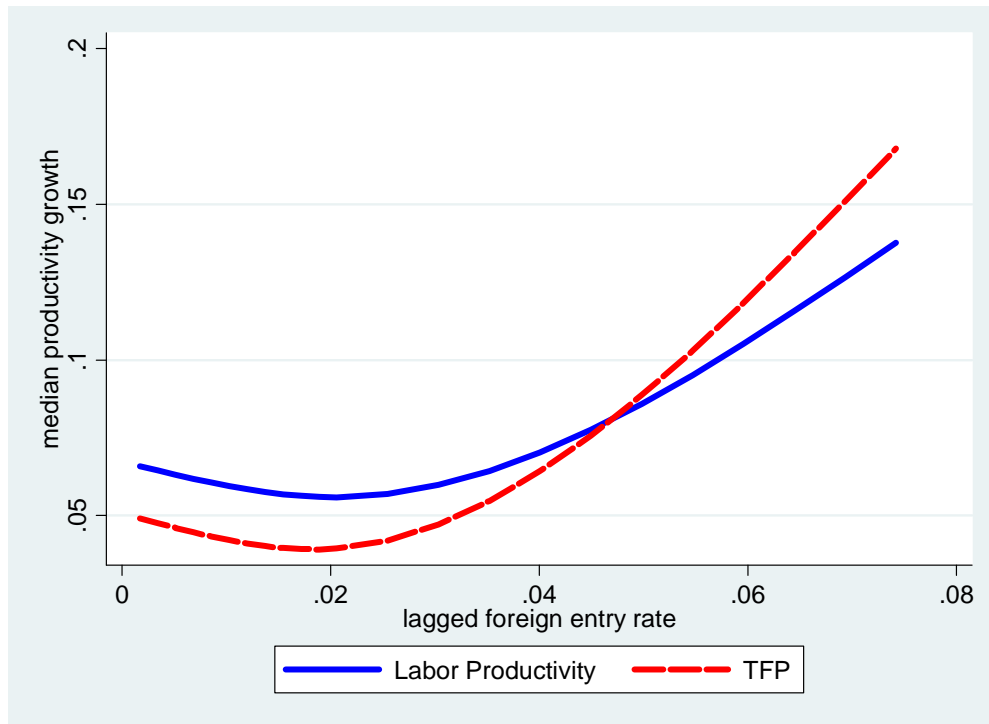
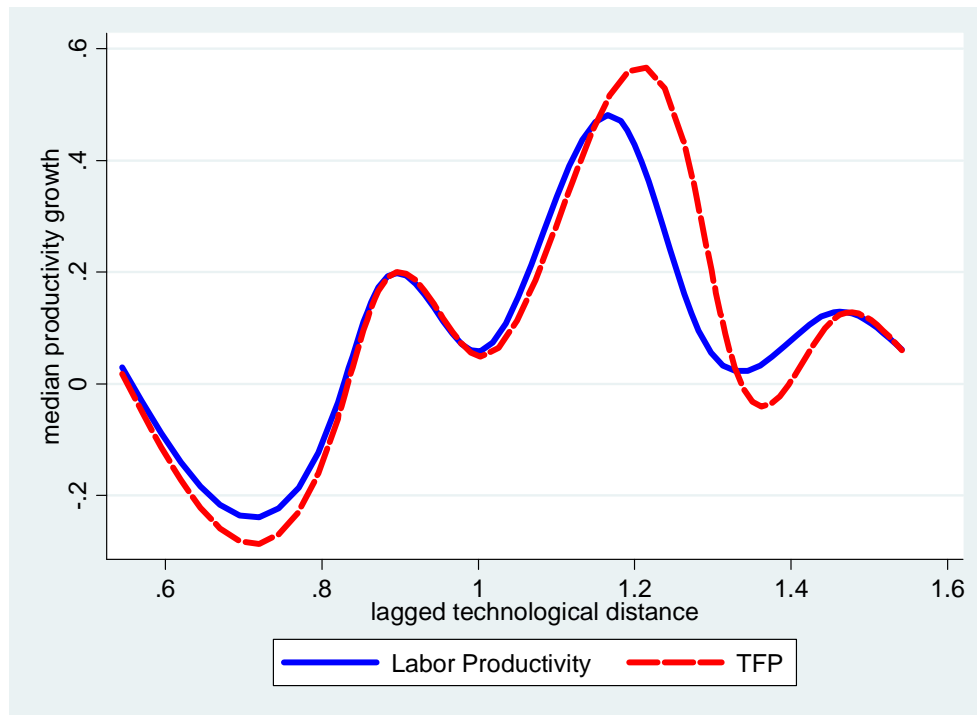


Figure 4-2 Technological Distance and Productivity Growth



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 or technological distance.

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

year	number of firms %		employment %		VA %		Sales %	
	<u>foreign</u>	<u>foreign+JVs</u>	<u>foreign</u>	<u>foreign+JVs</u>	<u>foreign</u>	<u>foreign+JVs</u>	<u>foreign</u>	<u>foreign+JVs</u>
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 Domestic industries' technological distance with foreign firms
10-year average, 1995-2004**

Top 5 domestic Industries with largest technological distance

SIC3	3-digit industry description	tech. distance
266	special chemicals	1.783
353	heavy lifters for transportation (general equipment)	1.773
368	medical instruments and equipment	1.721
361	mining, metallurgical and construction equipment	1.655
223	paper products	1.629

Top 5 domestic Industries with smallest technological distance

SIC3	3-digit industry description	tech. distance
395	home electronics	-1.022
134	sugar manufacturing	-0.550
345	metal products for construction and safety	-0.469
203	wood products	-0.420
431	metal waste processing	-0.416

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

Table 3 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
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
Growth of capital-labor ratio	0.098	0.448	-4.719	5.532
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 ¥1,000 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 4 Productivity growth models

Independent variables:	Dependent variable: gLP, growth of labor productivity			
	Pooled OLS		OLS w/ Fixed Effects	
	(1)	(2)	(3)	(4)
foreign entry (%), (t-1)	0.022 (0.087)	0.038 (0.100)	0.431*** (0.167)	0.439*** (0.166)
technological distance, (t-1)	0.146*** (0.046)	0.170*** (0.065)	1.139*** (0.393)	1.081*** (0.389)
entry(t-1) * distance (t-1)	-0.109 (0.080)	-0.116 (0.084)	-0.327*** (0.130)	-0.414*** (0.141)
growth of capital-labor ratio (t)	0.217*** (0.020)	0.215*** (0.020)	0.201*** (0.024)	0.142*** (0.025)
firm scale L (t)		-0.008 (0.009)		-0.393*** (0.051)
industry concentration (t-1)		-0.013** (0.021)		0.156*** (0.083)
constant	-0.088* (0.051)	-0.091** (0.121)	-1.353*** (0.467)	1.882*** (0.631)
industry dummies	No	No	Yes	Yes
year dummies	No	No	Yes	Yes
firm fixed effects	No	No	Yes	Yes
number of obs	4,505	4,505	4,505	4,505

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

Table 5a Productivity growth models: LP vs. TFP

Independent variables:	Dependent variable:		
	gLP*	gTFP1*	gTFP2*
	(1)	(2)	(3)
foreign entry (%), (t-1)	0.439*** (0.166)	0.511*** (0.183)	0.496*** (0.184)
technological distance, (t-1)	1.081*** (0.389)	1.201*** (0.430)	1.160*** (0.432)
entry(t-1) * distance (t-1)	-0.414*** (0.141)	-0.489*** (0.156)	-0.470*** (0.157)
growth of capital-labor ratio (t)	0.142*** (0.025)		
firm scale L (t)	-0.393*** (0.051)	-0.374*** (0.054)	-0.375*** (0.054)
industry concentration (t-1)	0.156*** (0.083)	0.185** (0.092)	0.187** (0.092)
constant	1.882*** (0.631)	1.668 (0.684)	1.722*** (0.688)
industry dummies	Yes	Yes	Yes
year dummies	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes
number of obs	4,505	4,505	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 $TFP=(VA/K)^a \times (VA/L)^b$, 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 5b Productivity growth models with Heckman correction of selection bias

Independent variables:	Dependent variable:			
	LP growth		TFP growth*	
	without correction	Heckman correction	without correction	Heckman correction
	(1)	(2)	(3)	(4)
foreign entry (%), (t-1)	0.439*** (0.166)	0.48*** (0.191)	0.496*** (0.184)	0.563*** (0.213)
technological distance, (t-1)	1.081*** (0.389)	0.958* (0.559)	1.160*** (0.432)	1.124* (0.622)
entry(t-1) * distance (t-1)	-0.414*** (0.141)	-0.513*** (0.204)	-0.470*** (0.157)	-0.594*** (0.227)
growth of capital-labor ratio (t)	0.142*** (0.025)	0.138*** (0.025)		
firm scale L (t)	-0.393*** (0.051)	-0.421*** (0.052)	-0.375*** (0.054)	-0.399*** (0.055)
industry concentration (t-1)	0.156*** (0.083)	0.149 (0.144)	0.187** (0.092)	0.201 (0.160)
constant	1.882*** (0.631)	2.019*** (0.735)	1.722*** (0.688)	1.736** (0.806)
industry dummies	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes
number of obs	4,505	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.

Table 5c 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)	0.439*** (0.166)	0.429*** (0.171)	0.263** (0.136)	0.496*** (0.184)	0.500*** (0.188)	0.301** (0.150)
technological distance, (t-1)	1.081*** (0.389)	0.987*** (0.369)	0.332*** (0.089)	1.160*** (0.432)	1.084*** (0.416)	0.355*** (0.010)
entry(t-1) * distance (t-1)	-0.414*** (0.141)	-0.394*** (0.148)	-0.223** (0.107)	-0.470*** (0.157)	-0.459*** (0.164)	-0.261*** (0.118)
growth of capital-labor ratio (t)	0.142*** (0.025)	0.092** (0.045)	0.198*** (0.043)			
firm scale L (t)	-0.393*** (0.051)	-0.652*** (0.096)	-0.030*** (0.011)	-0.375*** (0.054)	-0.573*** (0.093)	-0.029*** (0.012)
industry concentration (t-1)	0.156*** (0.083)	0.165** (0.085)	-0.081*** (0.036)	0.187** (0.092)	0.198** (0.095)	-0.079** (0.041)
constant	1.882*** (0.631)		-0.291* (0.175)	1.722*** (0.688)		-0.382** (0.198)
<i>Arellano-Bond AR2 test</i>		(0.111)	(0.117)		(0.039)	(0.049)
<i>Hansen J test</i>		(0.218)	(0.008)		(0.153)	(0.006)
industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
number of obs	4,505	2,818	4,505	4,505	2,816	4,502

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 5d Productivity growth models with stricter heterogeneity at firm level

Independent variables:	Dependent variable			
	LP growth		TFP growth	
	(1)	(2)	(3)	(4)
foreign entry (%), (t-1)	0.108 (0.100)	0.147 (0.101)	0.121 (0.112)	0.154 (0.112)
technological distance, (t-1)	0.904*** (0.045)	0.935*** (0.045)	0.991*** (0.050)	1.023*** (0.049)
entry(t-1) * distance (t-1)	-0.073 (0.056)	-0.104** (0.056)	-0.084 (0.062)	-0.111** (0.063)
growth of capital-labor ratio (t)	0.119*** (0.024)	0.168*** (0.023)		
firm scale L (t)	-0.321*** (0.048)		-0.279*** (0.051)	
industry concentration (t-1)	0.089 (0.070)	0.085 (0.071)	0.104 (0.078)	0.097 (0.078)
constant	0.631 (0.672)	-1.715*** (0.579)	0.297 (0.738)	-1.745*** (0.641)
industry dummies	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes
number of obs	4,505	4,505	4,502	4,502

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.