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. (2009) to analyze the impact of foreign entry on the productivity growth of domestic firms. In the face of foreign entry, domestic firms exhibit heterogeneous patterns of growth depending on their technological distance from foreign firms. Domestic firms with smaller technological distance from their foreign counterparts tend to experience faster productivity growth, while firms with larger technological distance tend to lag further behind. We test this hypothesis using a unique firm-level data of Chinese manufacturing. Our empirical results confirm that foreign entry indeed generates strong heterogeneous growth patterns among domestic firms.

JEL Classifications: D21, O3, F21
Keywords: Firm Heterogeneity, Creative Destruction, Productivity Growth, TFP, FDI, Entry, Competition, Chinese Economy

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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 through channels such as technology spillover. On the negative side, academics and policy makers alike, ever since Alexander Hamilton, time and time again, have warned the potential damages that foreign competition could have inflicted upon domestic industries and advocated industrial policies should be in place to protect domestic firms.[1] Yet, the debate so far has not taken firm heterogeneity into consideration. Inspired by the earlier works of Aghion et al. (2004, 2005b, 2009), 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, the entry of foreign firms could generate a divergent or heterogeneous impact on the growth of 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:

[1] One of the most recent examples is Larry Summers' expression of 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".

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 firms' heterogeneous behavior in their competition for survival, which follows similarly 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 refined their early argument by pointing out that it is too simple to assume incumbents will automatically surrender and be replaced; facing new competition, incumbents will fight for survival; and the likelihood of survival depends on the outcome of the competition. As such, new entrants' impact on incumbents is likely to be heterogeneous; and an important source of such heterogeneity is firm's technological distance to their new competitors. Aghion et al. (2009) empirically tested the relationship between heterogeneity and the divergent innovation and growth pattern generated by new entry using the UK manufacturing data, and the results seemed to have confirmed the hypothesis.

Our research is another attempt to use real-world data to test Schumpeter's theory of creative destruction. We are especially interested in finding out how foreign entry could potentially change the growth dynamics of domestic firms in a host country of FDI. We define the heterogeneity of domestic firms in terms of their relative technological distance from their foreign counterparts.[2] We hypothesize that the heterogeneity will in turn determine firms' behavior in response to foreign competition: Firms with relatively more advanced technology choose to compete neck-to-neck with foreign firms, while firms with relatively backward technology suffer a "discouragement effect" and lag further behind.

The contribution of our research is two-fold. First, it extends the framework of Schumpeterian "creative destruction" formalized by Aghion et al. (2009) to a setting of a large developing country: China. It is still an open question whether foreign entry generates a similar growth pattern in a transitional country, which is still on its path toward a more market-oriented economy. Second, we apply firm heterogeneity to the debate on FDI's impact on domestic firms. 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 gauging FDI's impact on domestic firms, we should pay more attention to the dynamic competitive environment that foreign competition helps to generate. 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

[2] Unlike Aghion et al. (2009), where they measured technological distance at industry level, we measure heterogeneity at the firm level.

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 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 failed to recognize the heterogeneity among 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 the FDI literature. In our view, including firm heterogeneity into our analysis captures the impact of foreign entry in a much more dynamic fashion, i.e., whether foreign competition can help a host country to generate a healthy competitive environment, which will benefit the country's economic growth in the long run.

The data for our empirical work is the firm-level data of Chinese Large and Medium Enterprises (LME) from 1995 to 2004, from Chinese National Bureau of Statistics. China's case is especially interesting for the following two reasons. First, it is one of the world's largest recipients of FDI.[3] 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

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[3] 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

the past 30 years has been nothing short of spectacle. 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 investments. To put things into perspective, by growing at a rate of 10% 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 growth 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 of our empirical results: we show with overwhelming evidence that foreign entry's impact on domestic firms is indeed heterogeneous, depending on domestic firm's technological distance with their foreign competitors. Foreign entry tends to generate a divergent growth pattern, in terms of TFP growth. Firms with larger technological gap tend to experience a much slower productivity growth than the firms with a smaller technological gap. This divergent growth pattern is robust to various estimation specifications. Even for domestic state-owned (or controlled) firms, such heterogeneous growth pattern is also well alive.

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

2. Empirical Model

To test the effect of foreign entry on productivity growth of domestic incumbent firms, we operate in the same direction as Aghion et al. (2009). The main difference between our empirical model and theirs is that we adopt stricter measurement of heterogeneity, i.e., we measure heterogeneity at firm level instead of industry level. This is illustrated in equation (3).

We test our hypothesis using the following estimation equation:

$$\begin{aligned} gTFP_{ijt} = \alpha + \beta_1 FE_{jt} + \beta_2 Tech\_Dist_{ijt-1} + \beta_3 FE_{jt} * Tech\_Dist_{ijt-1} \\ + X_{ijt}^{'}\gamma + \delta_j + \tau_t + u_i + \varepsilon_{ijt}, \end{aligned} \quad (1)$$

where i indexes the Chinese domestic firms that are without foreign investments, j indexes 3-digit industries in China's manufacturing sector, and t represents the year from 1995 to 2004. Productivity at the firm level is measured by total factor productivity, or TFP. Growth of TFP is simply $gTFP_{ijt} = \ln(TFP_{ijt}) - \ln(TFP_{ijt-1})$. On the right hand side of equation, FE_{jt} represents foreign entry rate at SIC 3-digit industry level, j; $Tech\_Dist_{ijt-1}$ measures technological distance between average TFP of foreign firms in industry j, and TFP of individual domestic firms in the same industry. We lag technological distance by one year to capture the initial technological gap before entry year t.[4] Finally, to capture the heterogeneous effect of foreign entry on domestic firms, as

[4] We chose not to use deeper lags as it will significantly reduce our observations in the regression.

in Aghion et al. (2009), we include an interaction term between foreign entry rate and relative technological distance, i.e., $FE_{jt} * Tech\_Dist_{ijt-1}$. We also include controls for industry effects, δ_j, time effects, τ_t, and firm fixed effects, u_i. We will discuss the rationale for each of these effects in Section 4, when we discuss our empirical results. Finally, we include $X's$ as a list of additional control variables. Again, we will explain why we pick these control variables in Section 4.

Now some more details about how we measure our key variables. We measure the foreign entry rate using the following formula:

$$FE_{jt} = \frac{\sum_{i=1}^{M_{jt}} L_{ijt,(D\_FJV=1)} - \sum_{i=1}^{M_{jt-1}} L_{ijt-1,(D\_FJV=1)}}{\sum_{i=1}^{N_{jt-1}} L_{ijt-1}}, \tag{2}$$

where L stands for labor employment; N_{jt} is the total number of firms in the 3-digit industry *j*, in year *t*; M_{jt} is the total number of foreign invested firms (where *D_FJV*=1), including both foreign wholly owned (F) and foreign-domestic joint ventures (JV), in the same industry. In words, we measure foreign entry rate in industry *j* by the employment change of foreign-invested firms relative to the total labor employment of all firms in the same industry, with domestic firms included. We use employment change, instead of actual investments, to capture the entry rate, because the data on investments tend to be very jumpy and noisy. Another advantage of our measure of foreign entry is that it not only captures the change from the new entry, but also picks up the change from the expansion of the existing foreign invested firms.

Technological distance, our key variable to capture firm-level heterogeneity, is measured by the difference of total factor productivity between average foreign firms in industry *j*, and individual domestic firms, *i*, in the same 3-digit industry:

$$Tech\_Dist_{ijt} = \ln(TFP_{jt}^{F}) - \ln(TFP_{ijt}^{D}) , \tag{3}$$

where *F* and *D* denotes foreign and domestic firms, respectively. Note that the first term in equation (2) is the average TFP of foreign invested firms in industry-year, *jt*, while the second term is the TFP of individual domestic firm, *i*, in industry-year, *jt*. This is where we differ from Aghion et al. (2009), in which they measured technological distance at the industry level only, i.e., both terms of productivity are indexed at *j*. We think our measure captures firm heterogeneity more accurately.

To compute firm-level TFP, we use the following formula derived from the Solow-type production function:

$$TFP_{ijt} = \frac{VA_{ijt}}{K_{ijt}^{\alpha} L_{ijt}^{\beta}} \quad , \tag{4}$$

where *VA* is value-added, *K* is net value of fixed assets after deprecation, and *L* is labor employment, with α, β being output elasticity of capital and labor, respectively. We first assume production function to be constant return to scale, i.e., α+β=1. So α, β are estimated from the following estimation equation:

$$va_{ijt} = \alpha k_{ijt} + (1-\alpha) l_{ijt} + \tau_t + a_i + \varepsilon_{ijt} , \tag{5}$$

where *va, k* and *l* are log transformation of *VA, K* and *L*; τ_t is time effect, a_i is firm fixed effect and ε_{ijt} is i.i.d. error term.

To check the robustness of our results, we also compute an alternative measure of TFP, called TFP2, in which we relax our previous assumption of constant return to scale, and allow capital-output elasticity, α, and labor-output elasticity, β, to be separately estimated in the following equation:

$$va_{ijt} = \alpha k_{ijt} + \beta l_{ijt} + \tau_t + a_i + \varepsilon_{ijt} \qquad (6)$$

Again, τ_t is time effect, a_i is firm fixed effect and ε_{ijt} is i.i.d. error term.

Now back to equation (1). Foreign entry rate, FE_{jt}, technological distance, $Tech\_Dist_{ijt-1}$, and their interaction, $FE_{jt} * Tech\_Dist_{ijt-1}$, are the key variables, which we focus on throughout our empirical analysis. Our priori expectations for these three key variables are as follows. Concerning the sign of foreign entry, because the results from the past 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 advantage of backwardness suggests that firms with initial lower productivity level should have the capacity to raise efficiency faster than their more productive counterparts. The sign of the interactive term is of our major interest in testing our hypothesis. 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: when technological distances between domestic and foreign firms increases, foreign entry tends to produce a *negative* impact on the productivity growth of domestic firms; When technological distance decrease, i.e., when domestic firms are relatively advanced, foreign entry tends to produce a *positive* effect on the productivity growth of domestic firms.

3. Data

The data for this research are drawn from the Industrial Survey of Large and Medium Size Enterprises (LME) conducted by China's National Bureau of Statistical (NBS). This is a mandatory survey and coverage is comprehensive for China's industrial sector. Our own calculation indicates that in 2002, the total output of the firms in LME accounts for 60% of China's total industrial output.

We construct an unbalanced panel of manufacturing firms from 1995 to 2004. We started with roughly 170,000 observations for a period of ten years. Since we only focus on foreign entry's impact on domestic firms, we dropped roughly 50,000 non-domestic observations and we are left with a total of 120,000 observations before doing further data cleaning. After eliminating outliers for our key regression variables, we end up with a panel of roughly 85,000 observations, across ten years. Finally, our calculation of growth rates and lag variables further reduce our observation to about 60,000.

To show the overall picture of foreign invested 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]

As joint ventures have always been a big part of China's FDI inflows, we define foreign-invested firms broadly to include both foreign wholly-owned and joint ventures. As shown in the table, foreign invested firms have played a huge role in China. In 2004, they accounted for 42% of total labor force in manufacturing, 41% of total output in terms of value-added, and 49% of total sales. Our calculation shows direct evidence that China's remarkable openness to foreign direct investments is a major difference in its comparison to other East Asia economies, such as Japan and South Korea. This fact also makes our study of foreign entry's impact on Chinese firms highly relevant.

Foreign entry rate is one of the key variables 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 for every 2-digit manufacturing industry. We find that the highest foreign entry, on average, were in industries such as sports goods, leather products, furniture, telecom and computer, plastics and apparel. This is in general in line with our expectations. The average entry rate across all manufacturing industries in 1995-2004 period was around 7.3%. Also note that the lowest foreign entry rate appears to be in the following industries: tobacco, ferrous metals, non-ferrous metals and chemicals.

[Figure 2 here]

Technological distance, $Tech\_Dist_{ijt}$, is another key variable in our estimation. As defined by equation (3), it is measured by the average TFP of foreign firms relative to the TFP of individual domestic firms in the same 3-digit industry, *j*. In Figure 3, we plot a histogram of technological distance. From the histogram, we see that close to 96% of observations has a technological distance that is greater than zero. This came as no surprise since most foreign invested firms tend to enjoy an advantage in their technology.

[Figure 3 here]

Table 3 provides the summary statistics for the variables used in our regressions. The average TFP growth of Chinese domestic firms during 1995-2004 is between 2.5% and 3.3%.[5] The average foreign entry rate at 3-digit industry level is around 2.5%. The average foreign entry rate is 2.5%, with a standard deviation of 15.4%. The average technological distance between foreign firms (industry average) and domestic firms is 1.67, which implies the average TFP for foreign invested firms is about 5.5 times of the TFP level of domestic firms.

[Table 2 here]

4. Empirical Results and Discussions

4.1. Benchmark Results

Our baseline regression results are presented in Table 3. In column (1), we first run a simple pooled OLS regression with the three key explanatory variables: foreign entry, technological distance, and their interactive term. The coefficient on technological distance is positive and significant, and the positive sign indicates that firms further from

[5] We calculated two alternative measures of TFP, as described in equation (4) and (5).

the technology frontier benefit most from *knowledge spillover*, as also evidenced in Griffith et al. (2004). Another possibility is that it simply reflects the "*catch-up effect*": firms further from technological frontier grow faster because their starting point is low. The coefficient on the interaction term is negative and statistically significant at 1% level, which sends us an early signal that foreign entry's effect on domestic firm' TFP growth may depend on their technological distance with foreign firms. However, for this simple specification, the coefficient on foreign entry is barely significant, with p-value≈0.13, nonetheless the sign is positive.

[Table 3 here]

In column (2), we run pooled OLS regression including 3-digit level industry dummies. As argued in Aitken and Harrison (1999), foreign entry itself may depend on industry characteristics. This is a potential source of endogeneity and may bias our estimates. For example, if foreign firms strategically choose to enter a less productive industry, our estimate for the impact of foreign entry on TFP growth may be biased downward. To avoid this problem, we add in industry dummies to control for industry-specific effects. After controlling for industry effects, all the coefficients now become statistically significant. In particular, the coefficient on foreign entry becomes highly significant and the sign remains positive. Our first run of the simplest specifications in column (1) and (2) offers us an early indicator that the story of "creative destruction" may indeed be well alive in Chinese manufacturing industries.

In column (3) and (4), we further test our hypothesis with firm fixed effects. The rationale for using fixed effects panel regression is that our firm-level regressors, i.e., technological distance and its interaction with entry rate, may be correlated with other time-invariant firm-level characteristics that we did capture in the regression. If this is the case, our estimators will again be biased. To verify that using fixed effects is justified, we first run Hausman test on fixed effect in comparison to random effect.[6] The Hausman test clearly rejects the null that the fixed-effect estimator is similar to random-effect estimator. Column (3) shows our estimation results with fixed effects, and column (4) shows the same regression but with industry effects included. Both results are very similar. All three key variables remain the same sign and statistically significant. In particular, the coefficient on the interactive term between foreign entry and technological distance remains negative and significant. As mentioned previously, this interactive term is designed to capture the impact of foreign entry on productivity growth conditional on the technological gap. The significant and negative coefficient directly supports our hypothesis that domestic firms exhibit a divergent growth patterns in response to foreign entry – in the face of foreign entry, when technological distance increases (i.e., with larger technological distance), the TFP growth for domestic firms decreases.

Finally, in column (5), we include time (year) effects in addition to industry effects and firm fixed-effects. Including time effects helps us to control for macro environment and other common time trends that could potentially drive firm's productivity growth. Combined with firm level fixed effects and industry effects, this is the strictest test for

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[6] Hausman test strongly rejects the null that two estimators are not systematic different, with chi-square being 6198.3 and p-value <0.01%.

our hypothesis. Again, the coefficient estimates of all three key variables are highly significant and stay the same sign.

4.2. Robustness Check

In this section we test the robustness of our previous estimation results. We first include a more robust error structure; then we add in additional control variables. Next, we adopt an alternative measure of TFP to check if our previous regression results are sensitive to different TFP measures. Finally, we narrow down our sample of domestic firms to state-owned-enterprises (or SOEs) only. In our LME dataset, over 50% of domestic firms are SOEs. Given the fact that the SOE's restructuring has played a vital role in China's transition to the market economy, we are interested in finding out whether foreign direct investments also helped to generate a similar dynamism among the supposedly less market-oriented domestic firms.

We report the results for our robustness checks in Table 4. In column (1), we use a robust error structure to re-estimate our regression in column (5) of Table 3. Not surprisingly, the standard errors in column (1) are larger, yet all the coefficients still remain highly significant. For simplicity, in the regressions to follow, from column (2) to (6), we only report the results with the robust error structure.

[Table 4 here]

In column (2), we include two additional control variables: firm size and industry concentration ratio. Firm size is measured by labor employment, in natural logarithm.

Industry concentration ratio is measured by the ratio of the sales of the top five firms of the 3-digit industry, to the total sales of all firms, in the same industry. We include these two variables because past research shows that firm size and industry-level competition also affect firm's TFP growth. As reported in column (2), the coefficient on firm size is negative and statistically significant. This indicates that smaller firms tend to enjoy higher TFP growth than larger firms. The coefficient on industry concentration is also negative and highly significant. We take this to mean that higher level of industry monopoly (or lower level of industry competition) is detrimental to firm's productivity growth.[7]

In column (3) and (4), we use an alternative measure for firm level TFP and re-run our previous regressions. Column (3) includes only the three key variables with firm fixed effects, industry effects and time effects. Column (4) includes firm size and industry concentration as additional control variables. The results barely budged, indicating our estimation results are robust to different measurement of total factor productivity.

Finally, in column (5) and (6), we focus on foreign entry's impact on China's SOEs only. Among 58,000 observations of domestic firms in our regression, around 34,000 observations are SOEs, close to 60%. We chose to define SOEs in a broader sense.

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[7] Aghion et al., in their 2005QJE paper, showed empirically that there exists an inverted-U relationship between level of competition and innovation activities. We test if a similar relationship exists between competition and TFP growth. This relationship was confirmed in our data and the results are reported in Table 5. We discuss in details the results in section 4.3.

Specifically, we not only include domestic firms that are officially registered as state-owned, but also those firms with the state as the majority owner or shareholder. The latter includes those domestic firms that are essentially controlled by the state, although there are officially listed as non-SOEs. This type of SOEs could take the form of cooperatives, joint-stock companies or shareholding companies. Due to such large percentage of SOEs in our sample, we think it would be interesting to find out whether SOEs behave in a similar fashion as domestic firms in general, i.e., whether they respond to foreign entry based on their technological gap with foreign competitors. For this purpose, we run a separate group of regressions with SOEs only. We report our regression results in column (5) and (6) in Table 4. Compared to the results in column (1) and (2), the coefficient on foreign entry becomes more positive (bigger) and the coefficient on the interactive term becomes more negative (bigger in absolute value). The change in the size of the two coefficients seems to suggest that the effect of foreign competition on the productivity growth of SOEs is actually more pronounced than domestic firms as a whole. This result is very interesting. It suggests that foreign entry seems to have helped Chinese SOEs to select out the winners and losers, expediting the cleansing process of the less productive firms.

4.3. Competition and Productivity Growth

In this section, we extend our previous estimation results further by testing how industry-level competition affects firm's productivity growth. Aghion et al. (2005) showed competition and innovation activities exhibit an inverted-U relationship. The relation says that more competition is good for innovation, but only to a certain level.

When there is too much competition, firms lose their incentives to innovate as they are unable to extract monopoly benefits from innovation. Does such relationship exist between competition and TFP growth in Chinese manufacturing industries? We test if such relationship exists by first creating a measure of industry-level competition. Previously, we had industry concentration ratio, which is essentially a measure of industry monopoly. To measure industry competition, we simply invert this ratio. To capture the curvature of the inverted-U relationship, we also include a square term of the competition measure. Our estimation results are reported in Table 5.

Column (1) and (2) show the results with industry concentration ratio; column (3) and (4) reports the results with competition. Note again that our competition variable is just the inverse of the industry concentration ratio. As shown in column (4), our results confirmed such relationship yet again: The coefficient on competition is positive and statistically significant, and the coefficient on competition-squared is negative and highly significant. As innovation is a big driver of firm's TFP growth, it's not surprising to find a similar relationship between competition and TFP growth. To interpret this, firms tend to have higher productivity growth as the industry competition level increases (the first derivative), but with higher and higher competition level (the second derivative), the rate of TFP growth increases at a slower pace; and when the competition reaches a certain level, the productivity growth may even decline.

5. Conclusion

In the paper, we test Schumpeterian "creative destruction" in a setting of a large developing country, using a large firm level dataset on Chinese large and medium-size enterprises. Our empirical analysis strongly supports our hypothesis that foreign entry tends to produce a divergent growth pattern amongst domestic incumbents. This heterogeneous growth pattern depends on firm's technological distance from their foreign competitors. Our results are robust to various econometric specifications, alternative measures of productivity growth, and different sample size.

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 "desirable" economic dynamism within FDI-host country. It is true that foreign competition generates both winners and losers, but in the long run, the restructuring spurred by the creative destruction process helps to nurture a healthy competitive environment. We find this is true even for a transitional economy that is still burdened with many relatively less inefficient state-owned enterprises. We end with a quote from economist Edmund Phelps,[8] "(The) 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."

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

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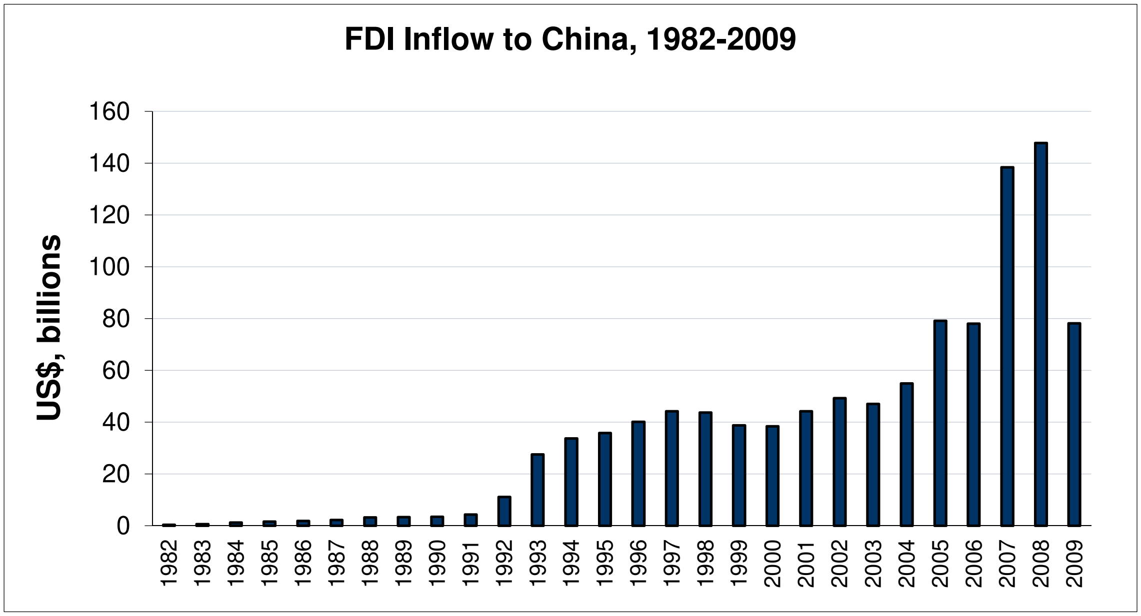
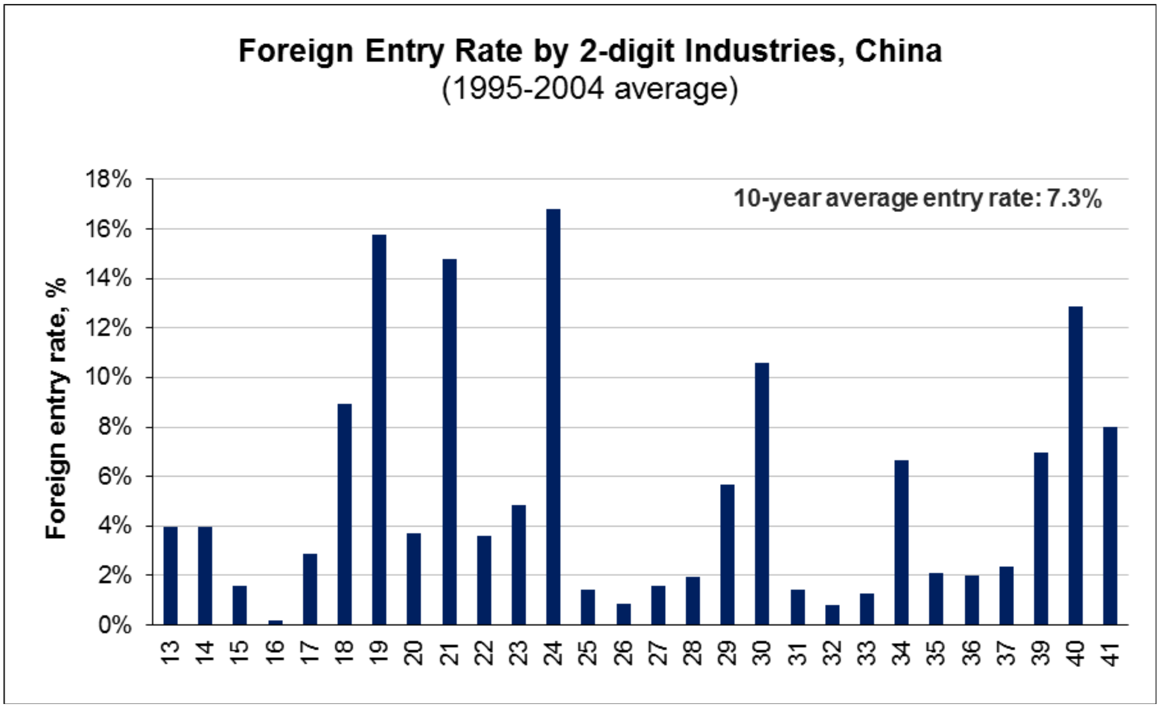
Figure 1: Foreign Direct Investment (FDI) to China, 1982-2009



Source: China's National Bureau of Statistics

Figure 2



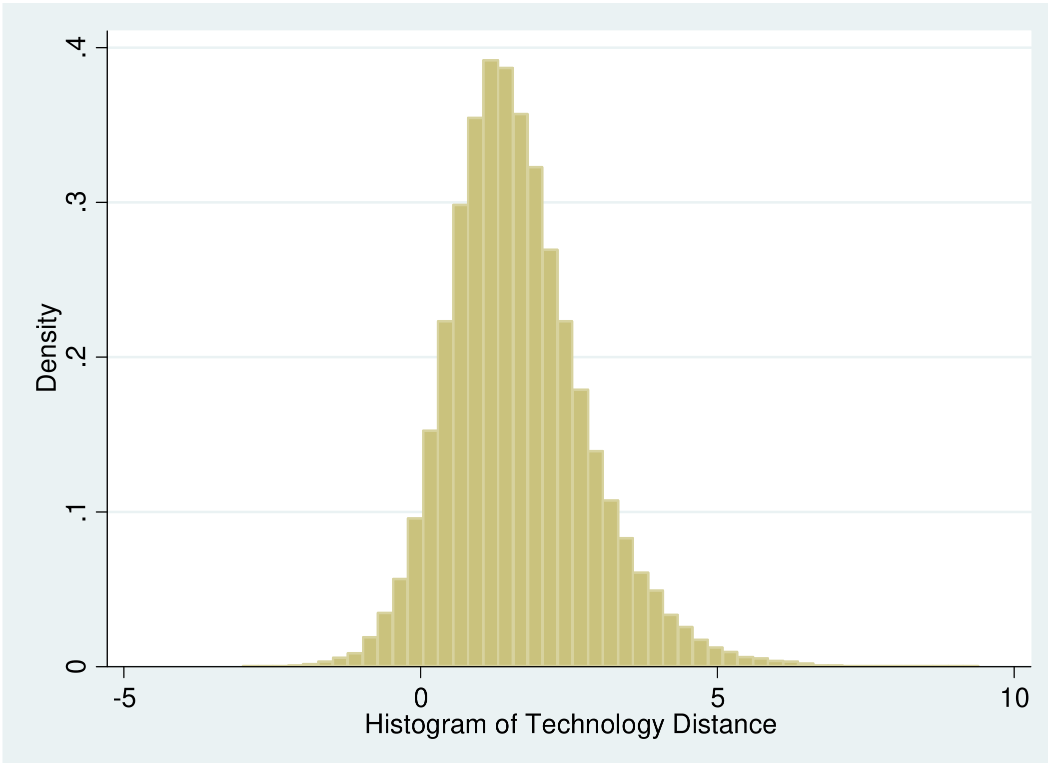
Descriptions of Chinese SIC 2-digit Industry Code

SIC-2	Industry Description	SIC-2	Industry Description
13	agriculture 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	sports products	40	telecom, computer, electronics
25	oil refinery	41	office equipment
26	chemicals		
27	medicine		

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

Figure 3 Histogram of Technological Distance (1995-2004)

(Percent (technological distance>0) = 95.6%)



Note: tech. distance is measured by the natural log of relative TFP difference. Refer to equation (3) for details.

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

Year	# of firms %	Employment %	Output %	Sales %
1995	17.1%	11.1%	19.4%	23.1%
1996	17.9%	12.2%	19.4%	24.2%
1997	35.1%	22.4%	29.2%	35.7%
1998	19.7%	13.8%	22.4%	28.2%
1999	21.9%	14.8%	24.0%	30.0%
2000	23.3%	17.0%	25.8%	32.3%
2001	27.8%	19.0%	28.5%	35.6%
2002	30.3%	19.7%	29.4%	35.6%
2003	44.8%	32.5%	36.2%	42.8%
2004	55.3%	42.2%	41.1%	49.2%

Source: Authors' own calculation based on China LME dataset, NBS.

Table 2 Descriptive statistics

	Mean	Std. dev	Min	Max
Total Factor Productivity, TFP*	14.87	19.94	0.07	666.87
Growth of TFP	0.033	0.624	-2.421	2.320
Total Factor Productivity, TFP2**	155.13	249.92	0.63	9028.09
Growth of TFP2	0.025	0.613	-2.782	2.429
Foreign entry rate	0.025	0.154	-0.465	2.196
Technological distance	1.67	1.09	-0.72	5.61
firm size	1427	3558	1	197048
Industry concentration ratio	0.28	0.15	0.04	1.00

Notes: *TFP is calculated following equation (5); **TFP2 is calculated following equation (6).

Table 3 Benchmark Estimates

	Dependent variable: gTFP, growth of total factor productivity				
	Pooled OLS		Fixed Effects (within estimation)		
Independent variables:	(1)	(2)	(3)	(4)	(5)
foreign entry	0.042	0.097***	0.077**	0.089***	0.086**
	(0.028)	(0.030)	(0.033)	(0.034)	(0.036)
technological distance, (t-1)	0.118***	0.146***	0.464***	0.470***	0.475***
	(0.002)	(0.003)	(0.005)	(0.005)	(0.005)
entry * distance (t-1)	**-0.039*** **	**-0.048*** **	**-0.084*** **	**-0.083*** **	**-0.090*** **
	(0.015)	(0.015)	(0.018)	(0.018)	(0.018)
constant	-0.155***	-0.315***	-0.712***	-0.352**	-0.417***
	(0.005)	(0.023)	(0.008)	(0.133)	(0.134)
industry effects	No	Yes	No	Yes	Yes
time effects	No	No	No	No	Yes
firm fixed effects	No	No	Yes	Yes	Yes
number of obs	57,961	57,961	57,961	57,961	57,961

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

Table 4 Robustness Check

	Dependent variable: gTFP, growth of total factor productivity					
	Robust Error Structure		Alternative TFP (TFP2)		SOEs Only	
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)
foreign entry	0.086**	0.079**	0.085**	0.074*	0.278***	0.251***
	(0.040)	(0.040)	(0.035)	(0.039)	(0.057)	(0.056)
technological distance, (t-1)	0.475***	0.470***	0.456***	0.454***	0.473***	0.468***
	(0.007)	(0.006)	(0.005)	(0.006)	(0.008)	(0.008)
entry * distance (t-1)	**-0.090*****	**-0.091*****	**-0.085*****	**-0.085*****	**-0.160*****	**-0.149*****
	(0.024)	(0.024)	(0.018)	(0.023)	(0.031)	(0.030)
firm size		-0.297***		-0.145***		-0.307***
		(0.016)		(0.015)		(0.022)
industry concentration		-0.305***		-0.282***		-0.422***
		(0.060)		(0.060)		(0.088)
constant	-0.417***	1.563***	-0.385***	0.607***	-0.348	1.763***
	(0.140)	(0.176)	(0.131)	(0.174)	(0.218)	(0.270)
industry effects	Yes	Yes	Yes	Yes	Yes	Yes
time effects	Yes	Yes	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
robust error	Yes	Yes	Yes	Yes	Yes	Yes
number of obs	57,961	57,961	57,961	57,961	34,029	34,029

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

Table 5 Competition and TFP Growth

	Dependent variable: gTFP, growth of total factor productivity			
	monopoly		competition	
Independent variables:	(1)	(2)	(3)	(4)
foreign entry	0.0791**	0.0724**	0.0904**	0.0689*
	(0.036)	(0.036)	(0.035)	(0.035)
technological distance, (t-1)	0.470***	0.472***	0.469***	0.474***
	(0.005)	(0.005)	(0.005)	(0.005)
entry * distance (t-1)	-0.0909***	-0.0902***	-0.0907***	-0.0913***
	(0.018)	(0.018)	(0.018)	(0.018)
firm size	-0.297***	-0.297***	-0.296***	-0.297***
	(0.010)	(0.010)	(0.010)	(0.010)
monopoly level	**-0.305*** **	**-1.501*** **		
	(0.056)	**(0.156)**		
monopoly level, squared		**1.535*** **		
		(0.186)		
competition level			**0.00731*** **	**0.0572*** **
			(0.002)	**(0.005)**
competition level, squared				**-0.00201*** **
				(0.000)
constant	1.563***	1.722***	1.456***	1.234***
	(0.148)	(0.150)	(0.148)	(0.149)
industry effects	Yes	Yes	Yes	Yes
time effects	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes
number of obs	57,961	57,961	57,961	57,961

Notes: *** (**, *) indicates statistical significance at the 1 (5, 10)-percent level. Competition level is measured by the inverse of industry concentration ratio.