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Inside the Virtuous Cycle between Productivity, Profitability, Investment and Corporate Growth: An Anatomy of Chinese Industrialization

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Abstract

This work explores the dynamics of the 'virtuous cycle' driving the impressive Chinese catching-up and growth by investigating of the micro relationships linking productivity, profitability, investment and growth, based on China's manufacturing firm-level dataset over the period 1998 - 2007. Interestingly and somewhat puzzlingly, we find that productivity variations, rather than relative levels, are the prevalent productivity-related determinant of firm growth. The direct relation between profitability and firm growth is much weaker as its contribution to the explanation of the different rates of firm growth is almost negligible. On the other hand, the profitability-growth relationship is mediated via investment. Firm's contemporaneous and lagged profitabilities display positive and significant effect on the probability to report an investment spike, and, in turn, investment activities are related to higher firm growth.

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JEL codes: D22, L10, L20, L60, O30

Keywords: Productivity, learning, market selection, profitability, investment spike, firm growth, catching-up, Chinese industry

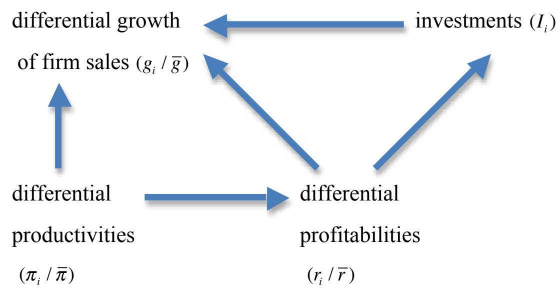
1. Introduction

The last three decades witnessed an impressive growth of the Chinese economy. Indeed, China undertook a deep and fast *great transformation* - borrowing Karl Polanyi (1944) expression - leading from a traditional mostly rural economy to an economy driven by industrial activities. In this work we explore the *microeconomics* of the evolution of the modern industrial sector, and the nature of the multiple links between (highly heterogeneous) firm-level productivities, profitabilities, investments and corporate growth.

Let us start by noting that the contribution to growth due to human capital accumulation and increased labor participation, although quite important in absolute terms, almost fade away when compared to the contribution due to productivity growth (Zhu, 2012). Firm level evidence further confirms such aggregate stylized fact and sheds new light on the microeconomics of catching-up of the Chinese economy: in another work (Yu et al. (2015); see also Brandt et al. (2012)) one shows that productivity increase due to improvements in (often restructuring) incumbents and (to a lesser extent) entrants has been the main source of productivity growth over the 1998-2007 period. On the contrary, the contribution to the aggregate productivity growth due to reallocation, that is inputs shifting from less to more productive firms, is remarkably small.

However, the accumulation of production knowledge and the process innovation underlying the impressive Chinese catching-up in productivity is only one element of the whole virtuous circle driving the "great transformation". Another crucial element is the influence exerted by the huge productivity differentials across firms upon corporate growth. In particular here, we focus on the effects of productivities, both in levels and growth rates, upon the patterns of firm growth in Chinese manufacturing over the 1998-2007 period. Together, we also investigate the role exerted by different governance and ownership structures. Moreover, we consider for the possibility that the relation between productivity and firm growth does not occur directly, but is mediated via profitability and investment in tangible assets.

In a nutshell we shall explore the following elements and relations of the virtuous circle of catching-up and growth:



Needless to say, the full analysis of the virtuous circle would require closing the increasing returns loop from investments and corporate growth to efficiency growth, but we leave this to another work.

In section 2, we offer a telegraphic outline of our empirical and theoretical points of departure. Section 3 describes data and variables. Section 4 discusses the relationship between relative productivities and corporate growth. Section 5 considers the influence of profitabilities upon investments and section 6 shows the impact of the latter on firm growth.

2. Empirical and Theoretical points of departure

Our empirical point of departure is the impressive heterogeneity that one observes across firms in all measures of efficiency irrespectively of the levels of disaggregation, the time window of observation and the country considered. This applies to developed countries (see, among others, Bartelsman and Doms, 2000; Dosi, 2007; Syverson, 2011), and even more so to emerging economies: we document and analyze the phenomenon in detail in the case of China in Yu et al. (2015). It is plausible to expect that such *persistent* heterogeneity ought to have some systematic, direct or indirect, effect upon corporate performances and in particular corporate growth.

Indeed, several models of industrial dynamics, from different traditions, predict heterogeneity in production efficiency and innovativeness to be fundamental drivers of the differential patterns of firms' growth. This is the case for "equilibrium models" such as Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995) and the more recent Luttmer (2007) and Acemoglu et al. (2013). And, even more so, this is a prediction of Schumpeterian evolutionary models, including the classic Nelson and Winter (1982), and also a family of models formally representing the process of selection among firms through some explicit mechanism of the replicator-dynamics type (see, among the others, Nelson and Winter, 1982; Silverberg et al., 1988; Dosi et al., 1995; Silverberg and Verspagen, 1995; Metcalfe, 1998).

There are two channels through which productivity may fuel firm growth. A first, *direct*, channel is that whereby more efficient firms gain market shares and grow more than competitors by setting lower prices. If competitiveness is inversely related to prices, and in turn prices are inversely related to productivity, the law of motion of a replicator type dynamic of shares of firms in any one industry is such that firms with above-average productivity should display above-average growth and increase their market shares, and vice versa for less productive firms.[1] A second, *indirect*, channel is that whereby more efficient firms operating in a competitive, price-taking market ought to enjoy higher profits and hence would invest more, especially in presence of imperfect capital markets, and consequently gain market shares at the expenses of competitors (Nelson and Winter, 1982; Bottazzi et al., 2001).

The evidence, however, on the ways higher relative efficiencies *directly* translates into higher firm growth is somewhat puzzling. Bottazzi et al. (2010) report that productivity levels of the firms have surprisingly low power in explaining the variance of firms' growth rates. On the contrary, the latter are mostly accounted for by time invariant unobserved variables ("fixed effects"), ultimately capturing also idiosyncratic degrees of "strategic freedom" of individual firms. Behind such a finding there are also technical reasons: it tends to happen when the explanatory variable, productivity levels in this case, is rather invariant over time and is collinear with the firm fixed effect (see Section 2.1 in Arellano, 2003). Hence resorting to plain fixed effects models washes away the contribution of the average efficiency of a firm over the observed period, which result in a systematic underestimation of the "true" contribution of the relative efficiency variable to relative firm growth. A procedure meant to alleviate the problem is proposed in Dosi et al. (2015) and it is aimed at extracting out of unobserved fixed effects the part which correlates with within-firm average productivities as distinct from the ture "independent" fixed effects. This is the analytical route that we shall also follow here.

Come as it may, there are also *indirect* channels through which higher efficiency might contribute to firm growth. One of them is mediated via profitabilities. If higher efficiency translates into higher profitability and, other things being equal, into higher cash-flows, then - under massive capital market imperfections,

[1] In this first approximation we do not mean to address the (hard) disentangling between *physical* productivity, and value added at constant prices, together with the device of the proper price index to deflate output (cf. Foster et al., 2008).

as it is the rule everywhere -, more internal financial resources untie financial constraints and hence allow the acquisition of more new-vintage investments, which might foster firm growth. In turn, if investments are a crucial mediating variable, their analysis is particularly tricky, due to the *lumpy* nature of investment activities at firm-level (cf. the seminal Doms and Dunne (1998) and the following stream of studies): years of inactivity or repair and maintenance are followed by one or several years of heavy investment, displaying some but limited synchronization with the industry business cycle (cf. Carpenter et al. (1998); Fagiolo and Luzzi (2006); Brown et al. (2009)).

Rather intuitively, large investment projects require correspondingly conspicuous financial resources. If those available internally are insufficient, the firm will have to rely on external finance to realize the project and this might lead to two consequences. *First*, the acquisition of new equipment and capital stock will be constrained, that is, the firm's desired level of investment will be curbed because of limited access to external finance (cf. Schiantarelli, 1996; Audretsch and Elston, 2002; Whited, 2006). *Second*, to the extent that investment is associated to firm growth, the existence of financial constraints will preclude the possibility to exploit opportunities for growth even when they notionally exist. Thus, limited access to external finance will constraint firm growth (see, among the others Oliveira and Fortunato, 2006; Whited, 2006). Notice in this respect that "imperfections" of the financial system tend to be more pronounced in an emerging economies such as China (see among the others Cull and Xu, 2003; Allen et al., 2012; Chen and Guariglia, 2013). In the following we shall investigate the relevance of financial constraints among Chinese firms, conditional on the different ownership structures. Indeed, incumbent evidence shows that they matter (Guariglia et al., 2011) especially in terms of constraints for the growth to private firms.

3. Data and Variables

This work draws upon firm level data collected by the Chinese National Bureau of Statistics (NBS). The database includes all industrial firms with sales above 5 million RMB covering period 1998-2007 and has already been employed in other empirical investigations, among others, Hu et al. (2005); Fu and Gong (2011); Yu et al. (2015).[2] Each firm is assigned to a sector according to the 4-digit Chinese Industry Classification (CIC) system that closely matches the Standard Industrial Classification (SIC) employed

[2]Industry is defined to include mining, manufacturing and public utilities, according to National Bureau of Statistics of China (NBSC). Five million RMB is approximately $US 600,000. The total output and value added are not available in 2004, thus, we do not use data for that year.

by the U.S. Bureau of Census.[3] Out of the comprehensive set of all firms, we focus on manufacturing firms only. Table **??** in the Appendix reports the list of the three digit sectors that have been employed in the analysis. We then apply a set cleaning procedures to the resulting set of data in order to eliminate visible recording errors (see Table A.1). We will refer to the final version of the database as "China Micro Manufacturing" (CMM).[4]

We are interested in corporate performances as revealed by several major dimensions, namely, productivity, profitability, investment rate and growth. Productivity $\Pi_{i,t}$ is the ratio of value added, at constant prices, over the number of employees, $\Pi_{i,t} = \frac{VA_{i,t}}{N_{i,t}}$, where $VA_{i,t}$ is real value added,[5] $N_{i,t}$ is the number of employees, of firm i at year t.[6] Labour costs $COL_{i,t}$ are defined as the sum of total wages and social security contributions. Our proxy for profitability is the ratio of gross profit margins, divided by output: $P_{i,t} = \frac{VA_{i,t}-COL_{i,t}}{Output_{i,t}}$.[7] Firm growth is measured as the log difference of (constant price) sales in two consecutive years: $G_{i,t} = \log Sales_{i,t} - \log Sales_{i,t-1}$. Firm's investment rate at time t is defined as the ratio of investment at time t and capital stock at time $t-1$. Investment is not directly reported in the data. Thus, we compute investment at time t as the difference of firm's fixed assets between time t and $t-1$.[8] The series of "real" capital stock are then computed following the perpetual inventory method, with the rate of depreciation 9% (as in Brandt et al., 2012). Table 1 reports statistics of the mean values of the variables of interest.

We identify seven categories of firms according to their ownership and governance structures. They

[3] In 2003, the classification system was revised. Some sectors were further disaggregated, while others were merged together. To make the industry codes comparable over time, we adopted the harmonized classification proposed in Brandt et al. (2012).

[4] We applied the following cleaning procedure. We dropped firms with missing, zero or negative output, value-added, sales, original value of fixed assets, cost of labour; and also firms with a number of employees less than 8, since below that threshold they operate under another legal system (Brandt et al., 2012). Finally, note that NBSC modified the industrial classification after 2002. In this paper we employ the industrial classification in use before 2003. Since CIC43 was emerged during the observation period, we do not consider it here.

[5] According to the definition of NBSC, value added = gross output - intermediate input + value added tax. Gross industrial output value: "the total volume of final industrial products produced and industrial services provided during a given period. It reflects the total achievements and overall scale of industrial production during a given period" (China Statistical Yearbook, 2007).

[6] Value-added is deflated by four-digit sectoral output deflators, from Brandt et al. (2012).

[7] We use output as the denominator instead of sales in order to be consistent with the NBSC methodology of computing value added, which is the difference between output and intermediate input. Also notice that the two variables, output and sales, are highly correlated, with a 0.99 correlation coefficient.

[8] According to NBSC, fixed assets include equipment and buildings.

Year	Number of Firms	Output	Employee	Value-added	Sales	Cost of Labour	Labour Productivity	Profitability	Growth Rates
1998	98407	49062	388	13188	45204	3231	43.58	0.165	
1999	98407	52462	372	14308	49158	3313	47.92	0.158	0.037
2000	100320	60023	366	16093	57406	3659	54.12	0.162	0.049
2001	93773	67435	351	18118	64520	3958	61.09	0.148	0.023
2002	114469	71179	322	19476	68042	3926	70.38	0.170	0.097
2003	121435	85401	314	23173	83380	4233	80.40	0.176	0.129
2005	210704	92236	250	24483	90387	4270	100.63	0.196	
2006	210704	112930	258	29971	111258	5111	121.70	0.195	0.177
2007	235380	131307	248	34715	129103	5923	142.51	0.202	0.198

Table 1: Summary statistics (mean) of dataset used in this paper. Source: our elaboration on CMM. Note: output, value-added, sales and cost of labour are reported at current price, unit: thousands yuan. Labor productivity is reported at 1998 constant price, unit: thousands yuan per employee. 2004 is not consider because output and value added are not available.

are State-owned enterprises (SOEs); collective-owned enterprises (COEs), Hong Kong, Macao and Taiwan-invested enterprises (HMTs); foreign-invested enterprises (FIEs), including foreign MNCs (FMNC) and joint ventures (JV) with a foreign share above 25%; shareholding enterprises (SHEs), that is State-private Chinese joint ventures; private-owned enterprises (POEs); and other domestic enterprises (ODEs). As reported in Table A.2, the original 23 registration categories have been aggregated in line with Jefferson et al. (2003).

4. Relative productivities and firm growth

Let us start by looking at the relationship between firm productivities and growth rates by means of a simple bivariate kernel regression. Figure 1 reports the productivity-growth relationship for three rather typical 3-digit sectors. The plots highlight the existence of a positive but mild relation between contemporaneous (relative) productivities and relative growth rates, well in line to what shown in Bottazzi et al. (2005).

In order to allow for a richer structure in the productivity-growth relationship, we employ a distributed lag (log) linear model with additive heterogeneity (Bottazzi et al., 2010; Dosi et al., 2015).[9] Based on sequential rejection of the statistical significance of longer lags structure, we choose as our baseline equation a model with one lag for productivity:

[9] Lagged values are required for the strict exogeneity of the error term imposed for consistency of standard panel estimators.

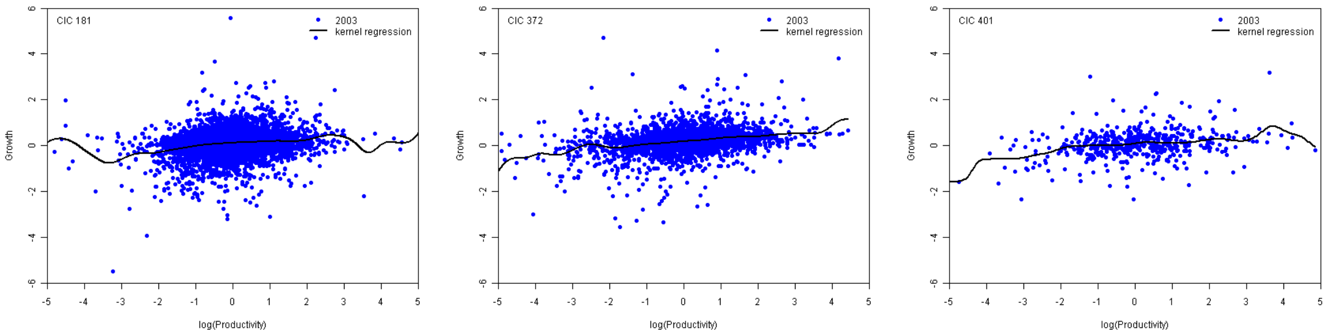


Figure 1: Productivity - Growth relationship in selected 3-digit sectors (textile clothing, automobiles and communication equipment) - kernel regression of 2003. Source: our elaboration on CMM.

$$g_{i,t} = \alpha + \beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + b_t + u_i + \epsilon_{i,t} \tag{1}$$

where $g_{i,t}$ denotes the growth rate of firm i in terms of log-differences of sales between two consecutive years, $\pi_{i,t}$ is the (log) labour productivity, b_t is a time dummy, u_i is a firm-specific time invariant unobserved effect, and $\epsilon_{i,t}$ is the error term. (Note that the presence of time dummies is equivalent to consider the variables in deviation from their cross-sectional average, so that what matters is only the relative efficiency of firms in the industry).

The fixed effect estimates of Equation (1) are available upon requests. In the majority of 3-digit sectors, the coefficients β_0 and β_1 are significant at the 1% level and have opposite signs, positive and negative, respectively. Such regularities in the two coefficients hold robustly across sectors. The distributions of parameters β_0, β_1 and $\beta_0 + \beta_1$ are shown in Figure 2.[10] The absolute values of the two coefficients are quite stable across sectors with median 0.2.

Despite the statistical significance, the coefficient estimates is not very informative on the extent to which firms are "selected", that is, how their market shares vary according to their relative productivities. To assess the strength of competitive selection, one needs to resort to a coefficient of determination to assess the proportion of the variance of firm growth explained by current and past relative productivities. Bottazzi et al. (2010) report in the case of Italy and France that the current relative productivity appears to "explain" roughly between 3% and 5% of the overall variance in growth, while the contribution of firm's unobserved idiosyncratic characteristics is much larger. In order to tell apart the effects due to average

[10]The "violin" reports a box plot and a kernel density to each side of the box plot.

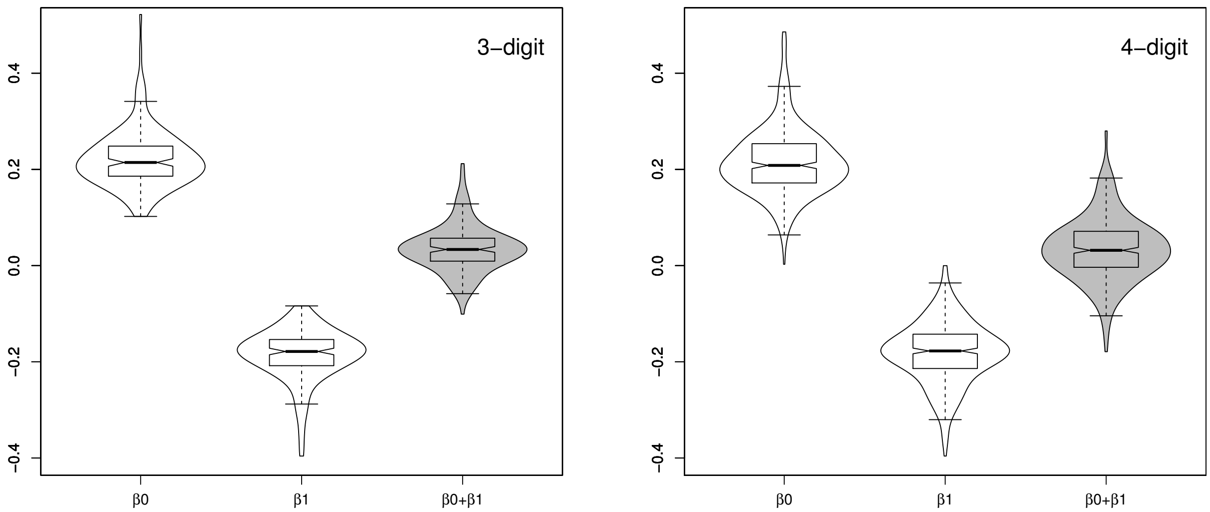


Figure 2: Productivity - Growth relationship at 3-digit and 4-digit sectoral level respectively. Distribution of parameters β_0, β_1 and $\beta_0 + \beta_1$ of the baseline model. The "violins" stand for distributions, median values and interquartile ranges, which have been calculated based on the fixed effect estimates of Equation (1).

productivity levels from "genuine" firm fixed-effects we disentangle within the unobserved effect u_i, the part which correlates with productivity from the part which does not (see also Dosi et al., 2015). It is then possible to re-estimate Equation (1) through a Correlated Random Effects model:

$$g_{i,t} = \alpha + \beta_0 \pi_{i,t} + \beta_1 \pi_{i,t-1} + \beta_{0a} \bar{\pi}_i + \beta_{1a} \bar{\pi}_{i,-1} + b_t + \mu_i + \epsilon_{i,t} \tag{2}$$

where $\bar{\pi}_i$ and $\bar{\pi}_{i,-1}$ are the within-firm time series averages of the (log) productivity up to time t and time $t-1$, respectively, while μ_i is the new unobserved firm-specific heterogeneity term, uncorrelated with the productivity regressors after controlling for their averages. The advantage with respect to Equation (1) is that we are explicitly taking into account the contribution to sales growth also of productivity averages over time. The random effects estimates from Equation (2) hardly change the value of the coefficients β_0 and β_1.[11]

However, our main interest lies in a measure of the fraction of total variance of firm growth explained

[11] Results are available upon requests.

	Labour Productivity				TFP			
	3-DIGIT		4-DIGIT		3-DIGIT		4-DIGIT	
	Mean (%)	Median (%)	Mean (%)	Median (%)	Mean (%)	Median (%)	Mean (%)	Median (%)
R^2	59.25	58.93	60.49	60.74	62.26	62.41	63.72	64.09
S^2	17.36	16.59	17.67	16.91	19.85	19.60	20.20	19.87
S^2_Δ	15.87	15.16	16.00	15.28	18.72	18.39	19.03	18.81
S^2_a	1.49	1.39	1.67	1.45	1.14	0.86	1.16	0.93

Table 2: Mean and medians of the distributions of R^2, S^2, S^2_Δ and S^2_a at 3-digit and at 4-digit levels respectively.

by productivity terms, and we compute it as follows

$$S^2 = \frac{Var(\beta_0\pi_{i,t} + \beta_1\pi_{i,t-1} + \beta_{0a}\bar{\pi}_i + \beta_{1a}\bar{\pi}_{i,-1})}{Var(g_{i,t})}. \tag{3}$$

while the conventional coefficient of determination of the overall fit of the model

$$R^2 = \frac{Var(\beta_0\pi_{i,t} + \beta_1\pi_{i,t-1} + \beta_{0a}\bar{\pi}_i + \beta_{1a}\bar{\pi}_{i,-1}) + Var(\mu_i)}{Var(g_{i,t})} \tag{4}$$

takes into account the contribution of the heterogeneity term μ_i, so that the difference between R^2 and S^2 delivers a measure of the variance explained by time invariant firm's unobserved effects.

Figure 3 shows distributions of the values of R^2 and S^2 together with S^2_Δ and S^2_a (i.e., the decomposition of S^2: S^2_Δ represents the part of S^2 due to productivity variation; S^2_a represents the part of S^2 due to average productivity level), across 3-digit sectors.[12] Our model with levels and averages of productivity plus firm-level heterogeneity is able to account for 55% - 65% of the variance in sales growth. The median of the R^2s is 0.53. The median value of S^2, capturing only the contribution of the productivity regressors (both levels and averages), is 0.17. That is, productivity variables appear to account for around one fifth of the variance in firms' growth rates. The explanatory power of productivity variables, hint at an important even if not overwhelming role of efficiency-driven competitive selection.[13]

The last four columns of Table 2 also show, for sake of robustness, the corresponding measures based on total factor productivity at 3- and 4- digit respectively, (however, see the caveats on TFP itself, discussed in Dosi and Grazzi (2006), and more specifically on China in Yu et al. (2015)).[14]

[12]The detailed values are available upon request.

[13]As an robustness check, this property also holds at more disaggregated level, 4-digit sectoral level. Mean and median statistics are shown in Table 2.

[14]The productivity measure is a Törnqvist index number, which does not require the estimation of any parameters.

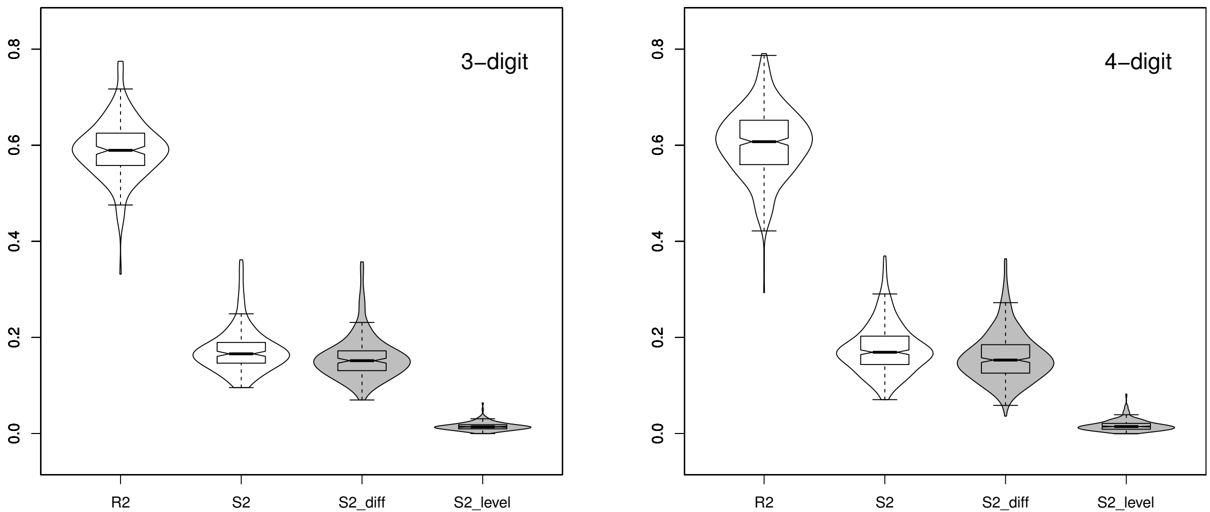


Figure 3: Productivity - Growth relationship at 3-digit and 4-digit sectoral level respectively. Distributions of R^2, S^2, S^2_Δ and S^2_a. The shaded violins refer to S^2_Δ and S^2_a. Distributions, median values and interquartile ranges are based on the values for 3-digit sectors.

It is well known that the ownership and governance structures of firms matter in terms of the different corporate growth patterns, and this is particularly true for the case of China (Guariglia et al., 2011). To study how different ownership structures affect the magnitudes of the explanatory power of productivity differentials we replicate the exercise above after splitting firms within the same 3-digit sector according to the seven ownership types (table 3 and figure 4). The values of S^2 of "Shareholding" (State-private joint ventures) and domestic private-owned firms are significantly higher than that of the others. Conversely, State-owned enterprises have significantly lower S^2, based on ANOVA and post hoc Tukey pairwise comparisons. That is, the selective power of market competition based on firms' relative efficiency is comparatively stronger in private and mixed ownership types, but is weaker among SOEs. Finally, we also investigated whether different "regimes" of technological learning, as captured by the Pavitt taxonomy (Pavitt, 1984), entails differences in the strength of the productivity-growth relation. Results do not broadly support such an hypothesis and are not shown here.

		Explanatory power of productivity for growth					
		(Mean)			(Median)		
Ownership	Number of sectors	S^2-mean (%)	$S^2_{\Delta\pi_{i,t}}$	$S^2_{\bar{\pi}_{i,t}}$	S^2-median (%)	$S^2_{\Delta\pi_{i,t}}$	$S^2_{\bar{\pi}_{i,t}}$
State-owned	108	14.37	11.88	2.50	13.64	11.10	2.12
Collective-owned	123	17.46	15.13	2.33	16.36	14.39	2.05
HMT-invested	104	14.48	13.11	1.38	13.88	12.41	1.05
Foreign-invested	113	15.47	14.30	1.17	14.44	13.39	0.92
Shareholding	119	18.73	17.02	1.71	17.98	16.33	1.53
Private-owned	143	21.47	20.05	1.41	21.16	19.81	1.18
Total	710	17.26	15.52	1.74	16.70	14.75	1.37

Table 3: Productivity - Growth relationship. Mean and median S^2 and decomposition of S^2 ($S^2_{\Delta\pi_{i,t}}$ and $S^2_{\bar{\pi}_{i,t}}$) by important ownership types (sectors with the number of firms for each ownership category greater than 200, only). Source: our elaboration on CMM.

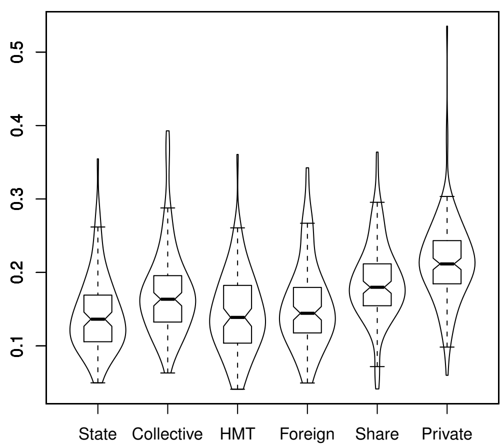


Figure 4: Productivity - Growth relationship. Distributions of S^2 by ownership types. Distributions, median values and interquartile ranges are shown in the violin.

4.1. Productivity levels and productivity changes

Due to the statistical regularities in the coefficients of the current and lagged productivities, one may conjecture that the actual drivers of firms growth are not the relative level of productivity at any time period, but rather productivity variations over time (Dosi et al., 2015). In order to test the conjecture, we decompose the S^2 of productivity into two components, associated respectively with levels and variations, and rewrite equation (2) as

$$g_{i,t} = \alpha + \beta_\Delta \Delta\pi_{i,t} + \beta_m \bar{\pi}_{i,t} + b_t + u_i + \epsilon_{i,t} \tag{5}$$

where $\Delta\pi_{i,t}$ is the growth rate of productivity of firm i ($\Delta\pi_{i,t} = \pi_{i,t} - \pi_{i,t-1}$), which accounts for the *growth* of productivity, and $\bar{\pi}_{i,t}$ is the within-firm average productivity level over t and $t-1$ ($\bar{\pi}_{i,t} = \frac{1}{2}(\pi_{i,t}+\pi_{i,t-1})$), capturing productivity *levels*.[15] If firms are selected and grow mostly driven by their relative productivity-level, the explanatory power of $\bar{\pi}_{i,t}$ should be greater than that of $\Delta\pi_{i,t}$, and conversely if the dominant impact is of the rates of change. The estimates continue to be based on a Correlated Random Effects model.[16] The shaded violins in Figure 3 display the distributions of $S^2_{\Delta\pi_{i,t}}$ and $S^2_{\bar{\pi}_{i,t}}$ and highlight how the variation of productivity ($S^2_{\Delta\pi_{i,t}}$) accounts for the larger proportion of S^2: the competitive selection mechanisms across firms within any one given industry appear to be driven to a greater extent by productivity *changes* rather than relative productivity *levels*.

5. Profitability and investment

Let us next investigate the impact of firms' profitability upon growth. Figure 5 shows the relationship between profitability and growth by means of a simple kernel regression. Notice that the kernel fit is flatter than in Figure 1, suggesting that the direct relation between profitability and growth is weaker than that found for productivity. This is confirmed by more rigorous parametric analysis. To allow for comparability of results we employ the same model as equation (1). The coefficients of current and lagged profitabilities are statistically significant for the majority of 3-digit sectors, as shown in Figure 6.[17] However, no strong statistical regularity concerning the signs and values of the coefficients emerges. Moreover, Figure 7 show

[15] Hence, $\beta_0 = \frac{\beta_m}{2} + \beta_\Delta$ and $\beta_1 = \frac{\beta_m}{2} - \beta_\Delta$.

[16] Results are available upon request.

[17] Results are available upon request.

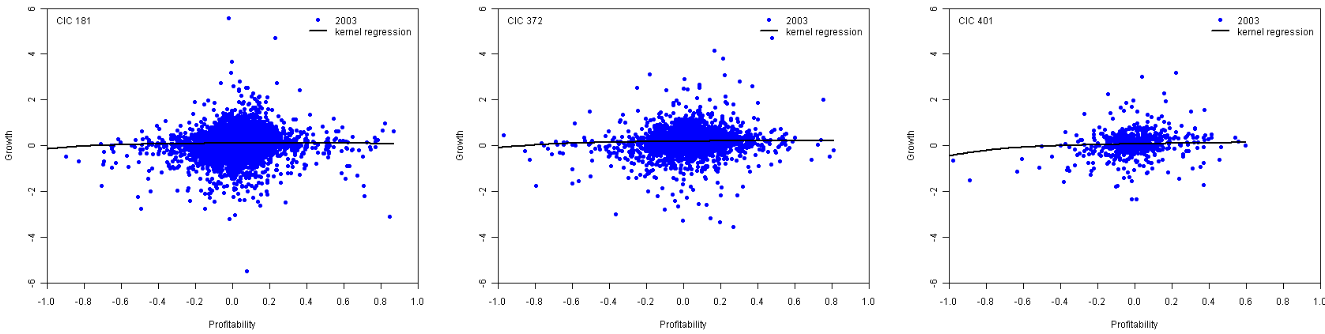


Figure 5: Profitability - Growth relationship in selected 3-digit sectors (textile clothing, automobiles and communication equipment) - kernel regression of 2003. Source: our elaboration on CMM.

the values of R^2 and S^2. The median of the overall "fitness" of the model is 0.55, while the explanatory power (S^2) of profitability variables on growth is 0.02 (median). Therefore, firms' unobserved idiosyncratic features appear to explain most of the variance in the (weak) profitability-growth relationship.

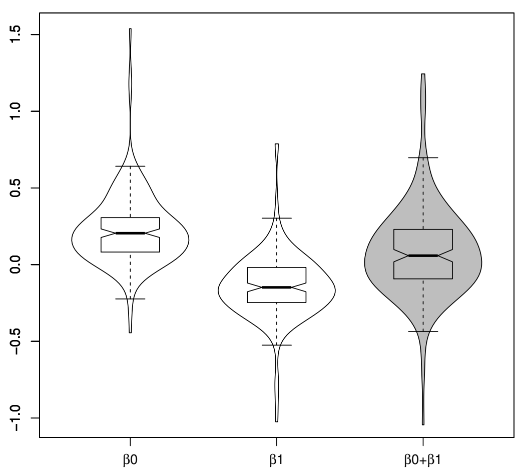


Figure 6: Profitability - Growth relationship. Distribution of parameters β_0, β_1 and $\beta_0 + \beta_1$ of the baseline model. Distributions, median values and interquartile ranges based on the values estimated for each 3-digit sector.

We distinguish firms in each 3-digit sectors by seven ownership types and estimate S^2 for each sub-sample. The mean and median values of S^2 are reported in Table 4 and the distributions are shown in Figure 8. Note that, the median S^2 is very small for all types of firms.

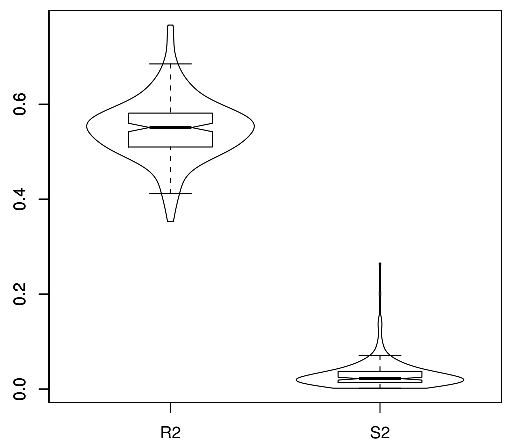


Figure 7: Profitability - Growth relationship. Distribution of R^2 and S^2. (Distributions, median values and interquartile ranges based on the values estimated for each 3-digit sector.)

Explanatory power of profitability for growth			
Ownership	Number of sectors	S^2-mean (%)	S^2-median (%)
State-owned	108	6.35	4.85
Collective-owned	123	3.81	2.53
HMT-invested	104	3.37	2.39
Foreign-invested	113	3.59	2.41
Shareholding	119	3.83	2.69
Private-owned	143	2.57	2.11
Total	710	3.85	2.68

Table 4: Profitability - Growth relationship. Mean and median S^2 among ownership types (sectors with the number of firms for each ownership category greater than 200, only). Source: our elaboration on CMM.

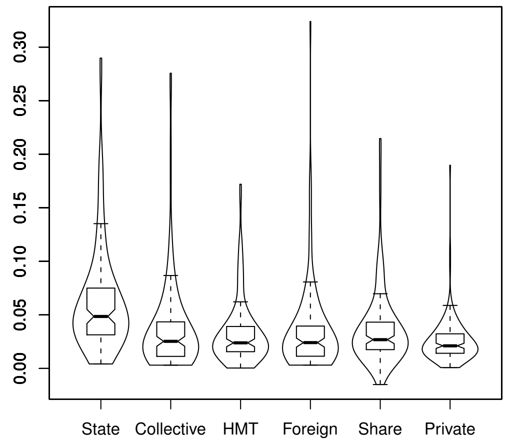


Figure 8: Profitability - Growth relationship. Distributions of S^2 of six important ownership types. Distributions, median values and interquartile ranges are shown in the violin plot.

Profitability appears to explain a modest 5% or less of the variance of growth rates of sales, which is much smaller when compared to the 17% of the explanatory power of productivity. Hence we ought to investigate a possible missing link between profitability and growth through the *indirect* channel of investment in tangible assets, which in turn would spur firm growth.

To our knowledge there does not exist to date a thorough investigation of the statistical properties of investment rates in China employing firm level data. Hence we start by looking at the statistical properties of proxies for that variable.

Figure 9 shows the distributions of investment rates, for selected years. For the majority of firms the *yearly* investment rate is very low, indeed as everywhere in the world: for example, in 1999, over 70% of firms reported an investment rate of 10% or lower; 9% of firms displayed an investment rate of 50% or more. These patterns are also quite stable over time: in 2007, 60% of firms reported an investment rate of 10% or lower; 15% of firms displayed an investment rate of 50% or more. Inactivity (zero investment) also occurs quite often: about 33.7% of the investment observations are zeros.

Figure 10 displays our (admittedly noisy) proxy for firms' investment over time. If we were to observe that, on average, the profile of annual firm-level investment were rather flat, that would corroborate the conjecture of a smooth process of capital adjustment at the firm level. The opposite would be true if we were to observe spikes in such firm level patterns. For each firm, we rank the investment shares for

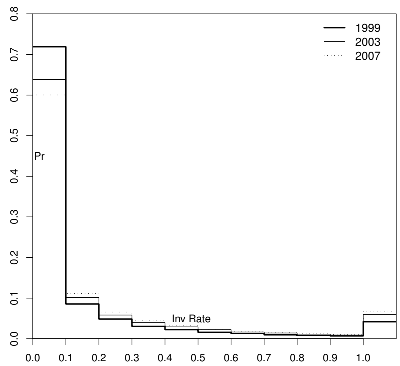


Figure 9: Histogram of investment rates in 1999, 2003 and 2007. Source: our elaboration on CMM.

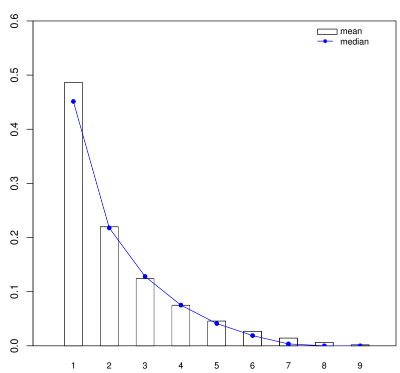


Figure 10: Average and median investment shares by rank (over firms in balanced panel (firm existing over the whole period 1998 - 2007). Source: our elaboration on CMM.

the period 1998-2007 and then we compute the average (median) for each rank over all the firms in the balanced panel. The highest investment share on average accounts for 50% of total investment during the nine years.[18] Firms concentrate 80% of investment in three years, while investment shares are significantly lower in other years, revealing a major lumpiness of the investment behavior. This confirms, of course, previous result on the dynamics of firms investments (see, among the others, Doms and Dunne (1998)).

Hence, let us focus on investment spikes (see among the others Power, 1998; Nilsen et al., 2009), because only very large investments episodes are likely to be accompanied by the expansion of production capacity, which, in this turn, is closely linked to firm growth. As a result, only investment rate above a certain

[18] Investment is deflated by price index.

	All	$S_{i,t} = 1$	$S_{i,t} = 0$	All	$S_{i,t} = 1$	$S_{i,t} = 0$	All	$S_{i,t} = 1$	$S_{i,t} = 0$	All	$S_{i,t} = 1$	$S_{i,t} = 0$
	1999			2003			2007			99-07		
Mean investment rate	0.16	0.80	0.04	0.22	0.96	0.06	0.24	1.04	0.08	0.21	0.94	0.06
Median investment rate	0.01	0.59	0.00	0.03	0.76	0.01	0.05	0.83	0.02	0.03	0.74	0.01
% of spikes in # of obs.	15.87			17.17			17.32			16.93		
% of total investment accounted by spikes	70.28			68.12			67.66			68.35		

Table 5: Descriptive statistics of investment spikes - determined by kernel rule. Note: $S_{i,t} = 1$ denotes the subsample of investment spikes, and $S_{i,t} = 0$ denotes non-spike observations. Source: our elaboration on CMM.

Size class	1999	2003	2007	Pooled	% Obs that are spikes
$<$ 20 employees	2.66%	2.40%	2.89%	2.66%	10.22%
20-300 employees	68.85%	73.74%	80.08%	75.03%	16.16%
300-1000 employees	21.69%	18.54%	13.43%	17.30%	19.57%
$\geq$ 1000 employees	6.81%	5.32%	3.60%	5.00%	22.82%
Number of obs	91,078	109,056	214,812	887,138	16.93%
Number of firms				346,749	

Table 6: Distribution of firms and investment spikes by size class. Source: our elaboration on CMM.

threshold will be classified as spikes. There are some criteria that guide the choice among different spike measures. As put forth in Nilsen et al. (2009) the investment must be large both respect to the history of the firm and to the cross section at averages of the industry. Further, it has to be a relatively rare event. Overall the definition of the spike must be able to account for a relevant share of total industry investment.[19]

In this work, we employ a non parametric methodology that, in order to identify firm level spikes, resort to the kernel estimate of the relation between investment and capital stock (Grazzi et al., 2015). Details are reported in the Appendix B. Descriptive statistics for kernel method are reported in Table 5. 18% of observations are classified as spikes and they account for 68% of total investment. Table 6 shows how firms and investment spikes are distributed across size classes.

[19]Nilsen et al. (2009) also hint at the necessity to account for the relationship that might exist between the investment rate and the capital stock. According to NBSC, the book value is the sum of nominal values for different years. We calculate the real capital stock using the perpetual inventory method, assuming a depreciation rate of 9% and deflate it.

5.1. Profitability and investment spikes

Conditional on firm's past investment behavior and on average investment behavior over the sample, what is the role of current and past profitabilities in shaping the capital adjustment patterns? The baseline model for estimating the relationship between profitability and investment employs autoregressive distributed-lags of length m,

$$y_{i,t} = \alpha + \sum_{s=1}^{m} \beta_s y_{i,t-s} + \sum_{s=0}^{m} \gamma_s x_{i,t-s} + b_t + c_j + u_i + \epsilon_{i,t} \tag{6}$$

where $y_{i,t}$ denotes investment rate of firm i at time t; $y_{i,t-s}$ represents investment rate at time $t-s$; $x_{i,t-s}$ denotes profitability at time $t-s$; u_i is a correlated firm effect; b_t are year dummies; c_j are 2-digit sector dummies, and $\epsilon_{i,t}$ is a serially uncorrelated disturbance.

Since our variable of interest is the investment spike $SPIKE_{i,t}$, that takes value 1 if there is a spike and 0 otherwise, we estimate the refinement upon our baseline model

$$SPIKE_{i,t} = \alpha + \beta_0 P_{i,t} + \beta_1 P_{i,t-1} + \beta_2 P_{i,t-2} + \beta_3 P_{i,t-3} + \gamma_1 D_{i,1} + \gamma_2 D_{i,2} + \gamma_3 D_{i,3} + b_t + c_j + u_i + \epsilon_{i,t} \tag{7}$$

where $P_{i,t}$, $P_{i,t-1}$, $P_{i,t-2}$ and $P_{i,t-3}$ are contemporaneous and lagged profitabilities and $D_{i,1}$, $D_{i,2}$ and $D_{i,3}$ are duration dummies capturing the time elapsed since last spike. $D_{i,1}$ takes value 1 if there is a spike in year $t-1$. $D_{i,2}$ takes value 1 if there is a spike in year $t-2$ but not in $t-1$. $D_{i,3}$ is 1 if there is a spike in year $t-3$ but not in $t-2$ or $t-1$. These dummy variables captures the effect of the length of the interval from the last high-investment episode on the probability of having a spike in year t (cf. Cooper et al., 1999; Grazzi et al., 2015; Bigsten et al., 2005). u_i is a firm-specific unobserved effect and $\epsilon_{i,t}$ is a serially uncorrelated logistic disturbance term. Ownership, time (year) and sectoral (2-digit) dummies are also included in the regression.[20]

The effect of profitability on the probability of having a spike in year t is reported in Table 7. The results of random effect logistic regression that controls for firm's heterogeneity are reported in column (v).[21] The

[20] After some experimentation and after comparing the AIC and BIC criteria of the models, we decide to include three lags of profitability.

[21] The results of logistic regression in column (vi) are very similar to column (iv). Robustness checks of the model are also reported in Table 7, column (i) through (iii). We exclude current profitability due to the endogeneity problem. The sum of the coefficients of profitabilities does not change significantly.

coefficients of current and lagged profitabilities are jointly significant, indicating that investment spikes are sensitive to profitability. Of course, the finding signals that internal and external sources of finance are not perfectly substitutable. The sum of the marginal effects of contemporaneous and lagged profitabilities is 0.074, meaning that one percent increase profitabilites will induce 7.4% increase in the probability of having an investment spike: a higher profitability increases the probability of carrying out investment projects. Expectedly, the effect of past investment spikes on the (negative) probability of having current investment spike decreases with time. Also the ownership structure of firms matters for the probability to undertake relevant investment projects. Taking State-owned enterprises as the reference group, all the coefficients of ownership dummies are significantly higher than in the former. In particular, the coefficient of private-owned enterprises is the largest, thus suggesting that this category of firms is the most active also in term of investment activity, also when controlling for current and past profitability levels.

6. Investment spike and firm growth

Investments in equipment embodying the latest technology is one of the drivers of productivity growth and plausibly, together, firm growth. In this respect, investments represent a further channel for the efficiency-driven competitive selection process. Mitigating that, it might also happen that very large investment episodes are associated with the disruption of consolidated production processes and existing organizational routines, thus having a negative effect on productivity and even sales growth, due to a long (and steep) learning curve. In particular, the recent empirical evidence (see for instance Power, 1998) has shown that the occurrence of negative effects following a spike is not a rare event, especially in the first years following the large investment episode.

To assess the effect of investment spike on firm performance we estimate the model

$$X_{i,t} = \beta_0 Dt0_{i,t} + \beta_2 Dt1_{i,t} + \beta_3 Dt2_{i,t} + \gamma_1 DBefore_{i,t} + \gamma_2 DLeast_i + b_t + c_j + u_i + \epsilon_{i,t} \tag{8}$$

where $X_{i,t}$ is one of the performance variables (productivity level/growth or sales growth), $Dt0_{i,t}$, $Dt1_{i,t}$, $Dt2_{i,t}$ are duration dummies. $Dt0_{i,t}$ takes value 1 if the investment spike is contemporaneous, occurring in year t; $Dt1_{i,t}$ is 1 if the investment took place at $t-1$, but not in t, and $Dt2_{i,t}$ takes value 1 if the spike occurred at $t-2$, but not in $t-1$ or in t. $DBefore_{i,t}$ is a dummy taking value one if the last investment spike was observed more than two years before t and zero otherwise, hence, the coefficient γ_1 accounts for

	Dependent Variable: Investment Spike											
	(i)		(ii)		(iii)		(iv)		(v)		(vi)	
	Random Effect Logit		Random Effect Logit		Random Effect Logit		Random Effect Logit		Random Effect Logit		Logit	
	Coef	Marginal Effects	Coef	Marginal Effects	Coef	Marginal Effects	Coef	Marginal Effects	Coef	Marginal Effects	Coef	Marginal Effects
P_t							0.359***	0.040***	0.274***	0.030***	0.273**	0.030**
							(0.120)	(0.013)	(0.100)	(0.011)	(0.127)	(0.014)
P_{t-1}	0.778***	0.070***	0.696***	0.063***	0.604***	0.054***	0.325**	0.036**	0.286**	0.031**	0.282**	0.031**
	(0.072)	(0.007)	(0.080)	(0.007)	(0.072)	(0.006)	(0.132)	(0.015)	(0.117)	(0.013)	(0.120)	(0.013)
P_{t-2}			0.182**	0.016**	0.066	0.006	-0.025	-0.003	-0.058	-0.006	-0.058	-0.006
			(0.077)	(0.007)	(0.072)	(0.006)	(0.088)	(0.010)	(0.088)	(0.009)	(0.068)	(0.008)
P_{t-3}					0.405***	0.036***	0.229***	0.025***	0.176**	0.019**	0.171**	0.019**
					(0.080)	(0.007)	(0.066)	(0.007)	(0.081)	(0.009)	(0.076)	(0.008)
Sum	0.778	0.070	0.878	0.079	1.075	0.096	0.888	0.098	0.678	0.074	0.668	0.074
Duration 1							0.877***	0.121***	0.800***	0.106***	0.822***	0.112***
							(0.025)	(0.005)	(0.030)	(0.005)	(0.026)	(0.004)
Duration 2							0.650***	0.085***	0.584***	0.074***	0.577***	0.074***
							(0.030)	(0.004)	(0.027)	(0.004)	(0.027)	(0.004)
Duration 3							0.401***	0.050***	0.345***	0.041***	0.342***	0.042***
							(0.033)	(0.005)	(0.030)	(0.004)	(0.030)	(0.004)
Collective									0.489***	0.058***	0.484***	0.059***
									(0.039)	(0.005)	(0.036)	(0.005)
HMT									0.480***	0.059***	0.475***	0.059***
									(0.045)	(0.006)	(0.041)	(0.006)
Foreign									0.504***	0.063***	0.499***	0.064***
									(0.045)	(0.006)	(0.043)	(0.006)
Shareholding									0.674***	0.087***	0.666***	0.087***
									(0.040)	(0.006)	(0.038)	(0.006)
Private									0.860***	0.116***	0.850***	0.116***
									(0.041)	(0.006)	(0.037)	(0.006)
Others									0.142	0.016	0.140	0.016
									(0.112)	(0.013)	(0.110)	(0.013)
Number of Obs	94622		94622		94622		94622		94622		94622	
Number of Groups	55647		55647		55647		55647		55647			
Brier Score							0.1150		0.1142		0.1142	
Pseudo R^2							0.0175		0.0257		0.0318	

Table 7: The effect of profitabilities and past investment spikes on current investment spikes. All models include year and sector dummies. Models (i) through (iv) are random effects logistic regression with bootstrap errors. Model (v) is pooled logistic regression with cluster errors. The table reports the results of both coefficients and marginal effects evaluated at the mean value of regressors, standard errors in parentheses. The reference group of ownership dummies is State-owned enterprises. Asterisks denote significance levels (***: p<1%; **: p<5%; * p<10%).

the effect of investment spikes on firm performance in the long run. The dummy $DLeast_i$ takes value 1 if firm i had at least one investment spike over the sample period and zero otherwise, hence it represents a sort of fixed effects for the group of firms reporting at least one investment spike. b_t are time dummies. u_i is, as throughout, a firm-specific unobserved random-effect and $\epsilon_{i,t}$ is the error term. Sectoral dummies are included.

Table 8 reports the estimates of the effects of investment spikes on productivity level. The positive coefficients (see columns (ii) and (vii)) of the dummy variable $DLeast$ reveal that the group of investing firms display higher productivity levels than their counterparts.[22] In model (ii), the overall contemporaneous effect of spikes on productivity level is $(Dt0 + DLeast)$ (0.427), and the effects of the latest past investment on productivity are $Dt1 + DLeast$, $Dt2 + DLeast$ and $DBefore + DLeast$ (0.400, 0.369 and 0.294). Thus, contemporaneous investments are associated with higher relative productivities: investments in tangible assets seem to be able to deploy their effect on productivity since their very adoption. Notice, finally, that the positive effect of investment spikes on productivity levels decreases with the time elapsed from last investment spike.

Table 9 displays the estimates of the effects of investment spikes on productivity growth. As shown in columns (ii) and (vii), the positive coefficients on the dummy variable $DLeast$ indicate that investing firms have higher productivity growth rates than the non-investing group. Notice that the effects of investment spikes on productivity growth are similar in magnitude amongst State-owned, HMT-invested and foreign-invested enterprises, while the other ownership types display stronger effects: possibly a circumstantial evidence of higher capital-embodied technical change in both "shareholding" and private Chinese firms.

Table 10 shows the effect of investment spikes on growth of sales. Firms having invested at least once during the sample period enjoy higher sales growth than their non-investing counterparts. The effect of contemporaneous investment spikes on firm growth is the largest (value of $D_{t0} + DLeast$ is 0.183 in column(ii)) and drops significantly afterwards. Rather interestingly, the strength of the investment - sales growth relationship is the lowest amongst State-owned enterprises: here probably restructuring and efficiency-enhancement is the major driver of investment.

[22] All the other models in Table 8 provide robustness checks.

	Dependent variable: Level of productivity						
				DLeast=1			
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
	RE	RE	FE	RE	FE	RE	RE
Dt0	0.251***	0.053***	0.086***	0.052***	0.062***	0.228***	0.055***
	(0.006)	(0.008)	(0.009)	(0.008)	(0.009)	(0.006)	(0.008)
Dt1	0.236***	0.026***	0.076***	0.024***	0.049***	0.213***	0.029***
	(0.006)	(0.009)	(0.010)	(0.009)	(0.010)	(0.006)	(0.009)
Dt2	0.216***	-0.005	0.067***	-0.008	0.035***	0.192***	-0.001
	(0.006)	(0.009)	(0.010)	(0.009)	(0.011)	(0.006)	(0.009)
DBefore	0.158***	-0.080***	0.037***	-0.084***	-0.009	0.140***	-0.067***
	(0.007)	(0.010)	(0.011)	(0.010)	(0.012)	(0.006)	(0.010)
DLeast		0.374***					0.321***
		(0.010)					(0.010)
Collective-owned						0.568***	0.549***
						(0.013)	(0.013)
HMT-invested						0.708***	0.689***
						(0.013)	(0.013)
Foreign-invested						0.894***	0.871***
						(0.014)	(0.014)
Shareholding						0.589***	0.566***
						(0.013)	(0.012)
Private-owned						0.689***	0.661***
						(0.012)	(0.012)
Others						0.566***	0.549***
						(0.030)	(0.030)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	279357	279357	279357	177428	177428	279357	279357
Number of firms	110052	110052	110052	65076	65076	110052	110052
R^2 - overall	0.1260	0.1299	0.0450	0.1102	0.0364	0.1775	0.1805
R^2			0.843		0.8274		

Table 8: Effect of Investment on levels of productivity. Note: Columns (i) and (ii) show random effects regressions. Column (iii) regards fixed effect ones. Columns (iv) and (v) are random effects and fixed effects regressions for a sub-sample firms with at least one investment spike. Column (vi) and (vii) are random effects regression with ownership dummies. Robust standard errors are in parentheses. Reference group of ownership dummies is State-owned enterprises. Asterisks denote significance levels (***: p<1%; **: p<5%; * p<10%).

	Dependent variable: Growth rate of productivity						
				DLeast=1			
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
	RE	RE	FE	RE	FE	RE	RE
Dt0	0.051***	-0.012*	0.018	-0.008	0.013	0.046***	-0.016**
	(0.004)	(0.007)	(0.011)	(0.007)	(0.011)	(0.004)	(0.007)
Dt1	0.021***	-0.042***	-0.002	-0.038***	-0.007	0.017***	-0.044***
	(0.005)	(0.007)	(0.011)	(0.007)	(0.012)	(0.005)	(0.007)
Dt2	0.008*	-0.055***	-0.004	-0.051***	-0.010	0.004	-0.057***
	(0.005)	(0.007)	(0.012)	(0.007)	(0.012)	(0.005)	(0.007)
DBefore	-0.004	-0.068***	-0.011	-0.062***	-0.019	-0.005	-0.067***
	(0.004)	(0.007)	(0.013)	(0.007)	(0.014)	(0.004)	(0.007)
DLeast		0.071***					0.069***
		(0.006)					(0.006)
Collective-owned						0.022***	0.020***
						(0.006)	(0.006)
HMT-invested						0.003	0.001
						(0.006)	(0.006)
Foreign-invested						-0.009	-0.012*
						(0.006)	(0.006)
Shareholding						0.024***	0.022***
						(0.006)	(0.006)
Private-owned						0.048***	0.045***
						(0.006)	(0.006)
Others						0.033*	0.031***
						(0.018)	(0.018)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	226010	226010	226010	142187	142187	226010	226010
Number of Firms	107626	107626	107626	63967	63967	107626	107626
R^2 - overall	0.0033	0.0037	0.0002	0.0038	0.0005	0.0041	0.0045
R^2			0.4201		0.3826		

Table 9: Effect of Investment on growth of productivity. Note: As Table 8.

	Dependent variable: Growth rate of sales						
				DLeast=1			
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
	RE	RE	FE	RE	FE	RE	RE
Dt0	0.159***	0.051***	0.081***	0.059***	0.078***	0.152***	0.049***
	(0.003)	(0.005)	(0.007)	(0.005)	(0.007)	(0.003)	(0.005)
Dt1	0.069***	-0.042***	0.014**	-0.035***	0.011	0.062***	-0.043***
	(0.003)	(0.005)	(0.007)	(0.005)	(0.007)	(0.003)	(0.005)
Dt2	0.035***	-0.076***	-0.007	-0.069***	-0.011	0.029***	-0.077***
	(0.003)	(0.005)	(0.007)	(0.005)	(0.007)	(0.003)	(0.005)
DBefore	0.006**	-0.109***	-0.011	-0.100***	-0.017**	0.003	-0.107***
	(0.003)	(0.005)	(0.008)	(0.005)	(0.008)	(0.003)	(0.005)
DLeast		0.132***					0.126***
		(0.004)					(0.004)
Collective-owned						0.044***	0.040***
						(0.005)	(0.005)
HMT-invested						0.046***	0.041***
						(0.005)	(0.005)
Foreign-invested						0.055***	0.049***
						(0.005)	(0.005)
Shareholding						0.055***	0.050***
						(0.005)	(0.005)
Private-owned						0.086***	0.080***
						(0.005)	(0.005)
Others						0.045***	0.041***
						(0.013)	(0.013)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	226010	226010	226010	142187	142187	226010	226010
Number of Firms	107626	107626	107626	63967	63967	107626	107626
R^2 - overall	0.0250	0.0282	0.0048	0.0283	0.0098	0.0269	0.0300
R^2			0.5543		0.5145		

Table 10: Effect of Investment on growth of sales. Note: As Table 8.

7. Final remarks

The whole virtuous circle driving industrialization and catching-up has many rich microeconomic facets which one is only beginning to explore. This paper contributes to that exploration in the case of China, an outstanding case of a rapid continent-wide *Great Transformation*.

Indeed, the major underlying driving force appear to be *learning*, that is the accumulation of technological and organizational capabilities yielding imitation, efficiency improvements and, eventually, innovation (see, in general, Cimoli et al. (2009) and, specifically on China Yu et al. (2015)). However, the ways such learning translates into corporate growth is somewhat more indirect and roundabout.

Our analysis reveals a few aspects of the "microeconomics of virtuous circle".

First, more efficient firms grow more, but *not so much more*. Market selection operates in the "right" direction, but in China as well as in fully industrialized countries, it appears to be relatively mild in its effects. That is, in an evolutionary language, (firm-specific) learning appears to be a much more powerful driver of industrial dynamics than sheer market competition and selection.

Second, the institutional set-ups matter a lot. They matter in terms of access to finance. And they matter also in terms of strategic orientations, forms of corporate governance, and ultimately growth performance. In the Chinese experience, there is some circumstantial evidence that State-owned enterprises appear to enjoy the softer financial budget constraints. However, State-private joint ventures turn out to be at the heart of Chinese industrialization in terms of productivity growth, placement among the most dynamic sectors and output growth.

This paper contributes to the literature on the market selection mechanism in an emerging market by exploring the extent to which firm growth rates are shaped by a) relative productivity levels and productivity variations, and b) profitability-related variables, respectively.

We find that, *first*, in both mechanisms, firms' fixed idiosyncratic "strategic orientations" play a prominent role in explaining the different patterns of firms growth.

Second, we have shown that productivity also greatly contributes to the "explanation" of firm growth. However it is the *growth* of productivity that accounts for a substantial portion of overall variance of firm growth rates, while firm's relative productivity levels seem to contribute less. As the argue at much greater length in Dosi et al. (2015), this finding is coherent with a statistical set-up in which different submarkets are aggregated in the "same" industrial sector. Firms located in different submarkets do not compete over the same products. Fiat and Volkswagen do not compete with Ferrari, Jaguar and Lamborghini. But they are all aggregated into the same "sector". As a consequence, however, mean productivities do not mean much. Thus, their different absolute levels of efficiency do not actually matter in explaining their different growth rates. What reveals some noisy competitive dynamics, on the contrary, is the dynamics on the relative levels of productivity themselves.

Quite interestingly, our results show that the productivity-growth link is stronger for the most dynamic firms of the Chinese economy, which often happen to be State-private joint ventures (shareholding enterprises).

Third, the direct contribution of profitability-related variables to growth is quite small even if not absent. The positive association between profitability and investment is as such evidence of the existence of financial constraints and financial market imperfection. In turn, investment spikes have a positive and significant effect on firms' productivity, both in levels and growth rates, and the effect on sales growth is even bigger. Taken together these results provide evidence in support of the mediating role of investment for firm growth, but, more generally, add to the anatomy of the roundabout ways the "virtuous circle" works, from learning and innovation all the way to investment and corporate growth.

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A. Table Appendix

Year	Original Dataset: Total	Original Dataset: Manuf. (CIC 13-42)	Output	Value Added	Sales	Original Value of Fixed Assets	Cost of Labour	Employment (< 8)
			Firms with missing, zero, or negative values, manufacturing firms only					
1998	165097	148664	5431	12239	5406	4555	11041	4237
1999	162010	146078	6111	10931	6115	4881	10562	5390
2000	162879	147249	5533	9342	5732	4615	9477	4708
2001	171187	155665	4216	7020	4492	3412	8905	3468
2002	181494	165801	4014	7877	4120	3163	8971	3194
2003	196154	181013	2672	5383	2654	2473	6674	2126
2005	271747	250975	1965	6212	1721	1501	5392	1884
2006	301873	278667	2044	5626	2138	2021	7261	2637
2007	336678	312304	1144	4928	1520	1768	10433	1790

Table A.1: Number of observations of the original dataset, number of observations with missing, zero or negative values for each variable, manufacturing firms only (CIC 13- 42).

Table A.2: Aggregation of the 23 registration categories. Source: Jefferson et al. (2003), Annex I.

Code	Ownership category		Code	Registration status
1	State-owned		110	State-owned enterprises
			141	State-owned jointly operated enterprises
			151	Wholly State-owned companies
2	Collective-owned		120	Collective-owned enterprises
			130	Shareholding cooperatives
			142	Collective jointly operated enterprises
3	Hong Kong, Macao, Taiwan-invested		210	Overseas joint ventures
			220	Overseas cooperatives
			230	Overseas wholly-owned enterprises
			240	Overseas shareholding limited companies
4	Foreign-invested		310	Foreign joint ventures
		Joint ventures	320	Foreign cooperatives
			340	Foreign shareholding limited companies
		Foreign MNCs	330	Foreign wholly-owned enterprises
5	Shareholding		159	Other limited liability companies
			160	Shareholding limited companies
6	Private		171	Private wholly-owned enterprises
			172	Private cooperatives enterprises
			173	Private limited liability companies
			174	Private shareholding companies
7	Other domestic		143	State-collective jointly operated enterprises
			149	Other jointly operated enterprises
			190	Other enterprises

B. Investment spikes definition

In the literature, there are four methods of identifying investment spikes, (i) absolute method: investment rate greater than 20% (the volatility of these ratio decreases with the capital stock, spikes are much common for small than for large firms); (ii) relative method; (iii) linear method and (iv) kernel method, which are summarized and compared by Grazzi et al. (2015). In this paper, we adopt kernel method to identify the investment spikes:

$$S_{i,t} = \begin{cases} 1 & \text{if } I_t/K_{i,t-1} > \alpha E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}] \\ 0 & \text{otherwise} \end{cases}$$

where α is set to 1.75 and the conditional expected value is obtained through kernel estimation within each 2-digit sector. For example, the threshold calculated by kernel regression for the overall sample is shown in Figure B.1. Investment rates above the threshold are defined as investment spikes.[23]

[23]In the data, 2% of firms have investment rate greater than 3. Thus, we delete firms with investment rate greater than 3 for at least one year.

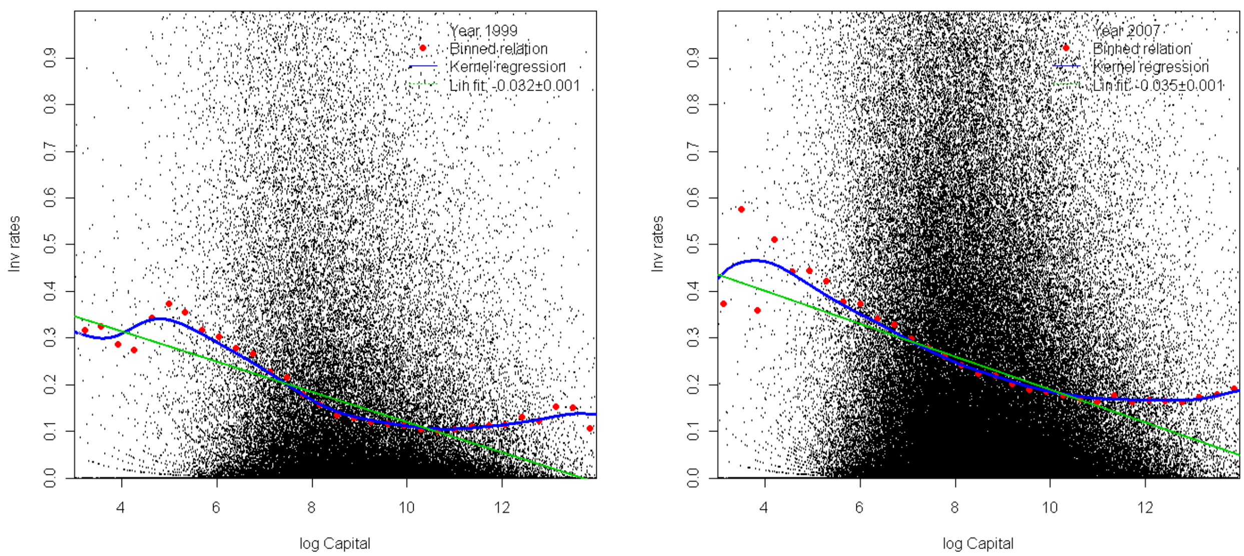

Figure B.1: Kernel regression (blue curve), binned relation (50 equal spaced bin; red dots) and OLS regression (green line) of investment rates (black dots) on log(capital) in 1999 and 2007. Source: our elaboration on CMM.