Labor regulation, Economic Complexity, and the China-India Gap[1]

Roger Gordon — UC San Diego
Wei Li — University of Virginia
Lixin Colin Xu — World Bank

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Abstract. Beginning with virtually identical per capita gross domestic product (GDP) in 1980, China's 2006 per capita GDP (purchasing power parity–adjusted) stands more than twice that of India's. We focus on explaining a key component of GDP per capita, productivity, using recent firm-level survey data. We focus on the role of labor regulation and its consequences in explaining China's productivity advantage. We believe that labor flexibility is a key explanation for India's productivity disadvantage, as it explains the predominance of small firms as well as the importance of firm size and city economic complexity (e.g., the sophistication of a city's industrial structure) in accounting for the Indian disadvantage in productivity. In addition, there is evidence that economic complexity has important threshold effects such that it does not matter in India due to its below the threshold but it matters a great deal in China due to its surpassing the threshold. Local economic complexity and human capital appear to be complementary. We also find direct evidence of labor distortion in India. Although in China we don't find a productivity dip around firms with 51–60 employees (after controlling for continuous trend), this pattern is found for Indian firms, especially in those pro-labor states. Pro-labor Indian states also feature lower share of large firms and share of firms immediately beyond the labor regulation threshold (e.g., 50-60 employees) than pro-employer states. Our empirical analysis suggests that labor regulations have far-reaching consequence on productivity, largely through the channel of firm size and the consequent economic complexity.

Key words: growth, policy reforms, productivity, labor flexibility, labor regulation, economic complexity, agglomeration, China, India.

JEL codes: O1, O4, O5, P5, K2, L5, L6, J4, G2.

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I. Introduction

While China and India are among the fastest-growing countries, a significant gap separates their growth during the past two and a half decades. In 1980, their per capita incomes were comparable. Since then, China's unprecedented growth, averaging more than 10 percent per year and showing no signs of slowing, puts it far ahead. India's gross domestic product (GDP) growth, though accelerating from 5.6 percent per year in the 1980s to 6 percent in the 1990s, and somewhat higher since (Srinivasan 2003, table 3), failed to keep pace. The International Monetary Fund and the Central Intelligence Agency World Factbook puts China's per capita GDP (purchasing power parity (PPP)–adjusted) at about $7,700 in 2006, but India's was at only $3,800, which is about half. Figure 1 shows the evolution of the gap at PPP exchange rates. If India is to catch up, it is critical for policy makers to understand the reasons behind this growth gap, a key task for development economists.

While the research question is at the macro level, we cannot rely on macro-level analyses because of data constraints: we have at most about 30 years of data. We therefore resort to micro data at the firm level. For the micro counterpart to GDP per capita, we opt to use total factor productivity (TFP) as the firm outcome variable. The reason is that it is perhaps the best firm-level link to macro economic performance. Indeed, TFP has been shown to be a major source of output growth (Solow 1957; Jorgenson and Griliches 1967). Moreover, TFP levels are highly correlated with income per capita (Hall and Jones 1999).

With firm-level information, we can transcend the constraint of macro data by examining cross sectional as well as temporal variations. We can link firm productivity to key city-level variables, such as skills, regulation, and other variables. Relying on insights from some recent developments in the growth and development literature, we explore a prevalent conjecture that labor regulation likely is a key bottleneck in India. In particular, we focus on the interplay between labor regulation, human capital, and economic complexity in explaining the China advantage in productivity over India.

Our firm-level data are from comparable samples of manufacturing businesses in the two countries used in the World Bank–sponsored Investment Climate Surveys conducted in 2003. The Indian survey covers 1,860 manufacturing establishments sampled from the country's top 40 industrial cities and major exporting industries. The Chinese survey covers 2,400 enterprises sampled from 18 cities and five regions. The survey results are for 2000 to 2002. We have data on the local business and policy environment of each establishment as of the survey year, including labor market practices, indicators of the level of skills, and a proxy of local economic complexity.

Several stylized facts emerge readily from basic comparison of China and India. Chinese firms have much higher productivity, are significantly larger (with a median of 134 in China versus 18 in India), and have more staff that use computer. Indeed, around 80 percent of sample Indian firms employ fewer than 50 employees, while only around 20 percent of Chinese sample firms are this small. And Chinese cities feature a much higher economic complexity (e.g, production and technological capacity to produce sophisticated products and ideas), as proxied by the share of large firms. India's smaller firm sizes and lower economic complexity are likely the results of its tight labor regulation.

Pooled firm-level regressions for the two countries indicate that both skills and economic complexity are important in explaining productivity. Moreover, economic complexity are productivity-enhancing only after it becomes sufficiently large, which explains why it does not affect productivity at all in India, but hugely so in China. The force of economic complexity in China is made even more potent by its complemenarity with skills. Indeed, when we allow for separate effects of skills and economic complexity in each country, they only matter in China. Thus stringent labor regulations have strong adverse effect for productivity in India—through its effects in reducing firm sizes, in reducing economic complexity, and in reducing the return to skills indirectly. Indeed, our productivity accounting exercise based on our regressions suggest that the primary source of China's productivity advantage is economic complexity, followed by firm size, and skills. The complementarity of skills and economic complexity is important in accounting for the China-India productivity differential. We obtain direct evidence of labor distortion in India. Although in China we don't find a productivity dip around firms with 51–60 employees (after controlling for continuous trend), this pattern is found for Indian firms, especially in those pro-labor states. Pro-labor Indian states also feature lower share of large firms and lower share of firms immediately beyond the labor regulation threshold (e.g., 50-60 employees) than pro-employer states.

Our paper confirms two key insights of Adam Smith: invisible hand and division of labor are the keys behind the wealth of nation. In our case here, visible hands of labor regulation leads to smaller firms and a less complex economic structure, therefore a less refined division of labor, which proves to be the key explanation behind India's disadvantage in productivity behind China.

The paper is related to three strands of literature. The first is the literature on the China–India comparison in economic performance. The China–India context is clearly important as they are the two most successful reform countries in the past two decades, and they account for one-third of the world's population. Bosworth and Collins (2007) and Dong and Pandey (2008) use macro (sector-level) time series data to conduct growth-accounting exercises to compare China and India's productivity growth patterns. Hsieh and Klenow (2009) use micro data to quantify resource misallocation in China and India and find substantial gains from correcting resource misallocation in both countries, with gains in India substantially larger. We differ in trying to find policy determinants that explain India's disadvantage in performance, in particular, the role of labor regulations in explaining India's size distribution, economic complexity, and ultimately productivity.

The second literature links Indian economic performance with its labor market flexibility. Besley and Burgess (2004) use state panels of India to investigate the impact of labor regulation on state economic performance and find that pro-labor regulations hinder economic performance. Aghion et al. (2008), linking the elimination of the system of industrial regulation with state-industry-level performance over time in India, find the growth effects of delicensing to be significantly stronger in states with pro-employer labor regulations than in pro-worker environments. Amin (2009) find that cumbersome labor regulation in India is associated with smaller firm sizes and more informality in India. Adhvaryu et al. (2010) find that Indian states facing more flexible labor regulation tend to adjust their labor to a great extent facing rain shocks, and this labor regulation effect exists only for large firms (e.g., firms with more than 50 employees). Our new insight is that labor inflexibility, through affecting firm sizes, further reduces economic complexity, which not only is the primary reason explaining India's productivity disadvantage but also reduce the return to local human capital indirectly.

The third and related strand is the relationship between labor regulation and firm productivity in general. Recent new firm-level studies of labor regulation have added great insights to the effects of labor regulation on economic performance (see Xu forthcoming for a summary). They suggest that labor regulation reduces firm sizes and increase the share of informal firms in the economy (Amin 2009; Almeida 2005; Almeida and Carneiro 2009), increase the discrepancy between labor costs and labor productivity (Petrin and Sivadasan 2006), reduces dynamic efficiency by reducing job turnover, especially in those more dynamic industries (Haltiwanger et al. 2008). This paper underlines a key mechanism neglected by the previous literature: economic complexity, which potentially has the power to explain a huge part of countries' productivity differential, both directly and indirectly (through its effects on the return to human capital). Relatedly, this paper is related to the endogenous growth literature (Romer 1986, 1990; Lucas 1988; Jones and Romer 2009), which argues that ideas and technological changes are endogenously determined and they ultimately determine national economic performance. Here, by comparing the two largest countries' productivity differential, we find that labor institutions determine economy of agglomeration and its interaction with human capital, which almost fully explain the productivity differential between the two countries.

II. Labor regulations in India and China

Many economists conjecture that labor market inflexibility could be an important reason behind China's advantage over India (Clark and Wolcott 2003, Bardhan 2006). It is thus useful to understand the differences in labor regulation between the two giants. The two giants actually started with similar labor relations in late 1970s. Both India and China have suffered from excessive government-directed resource allocations. However, the two country now differ markedly in labor regulation.

China has adopted reforms liberating labor markets beginning from the mid 1980s. Before the reforms, state-owned enterprises had little discretion in setting wage, employment level, and firing workers (Xu 2000). Since the enterprise reforms in the late 1980s, however, state-enterprises had gained substantial freedom in all aspects of labor decisions. More importantly, for the purpose of this paper in which we are only dealing with private firms, private firms have always enjoyed almost complete freedom in hiring and firing, wage setting, and other labor issues. In addition, there are no specific laws that explicitly restrict firm size for certain or all industries. It is widely believed that Chinese firms in the past decade had enjoyed much more flexibility than Indian firms in adjusting staffing levels to product market and technological developments (Ahya and Xie 2004; Bardhan 2006; Dong and Xu 2009).

In contrast, India has long-standing heavy-handed labor regulations since its independence.[2] All Indian states started with the same central regulation, the centerpiece of which is the Industries (Regulation and Development) Act of 1951 which states, "it is expedient

[2] For an excellent introduction of labor regulations in India, see Besley and Burgess (2004), of which we draw heavily in the following paragraphs.

in the public interest that the Union should take under its control the industries in First Schedule" (this enumerates all the key manufacturing industries at that date). No formal amendments to this act have been added to this act. Thus, industries in different states of India are subject to a common set of industrial policies (except in industrial relations). Since India's entry regulation reserve "a large number of products for small-scale industries (more than 600 such products reserved for this sector even now)" (Bardhan 2006), India's regulation of entry contributes to Indian firms' small sizes.

Features of labor regulation in India further limit firm size. Since India is a federal democracy, Indian central and state governments have joint jurisdiction over labor regulation legislation. The foundation of central legislation is the Industrial Dispute Act of 1947, which spells out the conciliation, arbitration and adjudication procedures to be followed in case of an industrial dispute. The Act intends to offer some protection against exploitation by employers for workers worked in the organized sector. This Act has been extensively amended by local governments during the post-independence period. As a result, Indian states feature tremendous variations in the stringency of labor regulation, ranging from pro-employer, to neutral, and to pro-worker environments (Besley and Burgess 2004).

The existing labor codes in India require businesses that have more than a threshold of employees, 50 in most states, to seek the state government's permission for closure or the retrenchment of workers, and permissions are rarely granted (Sachs, Varshney, and Bajpai 1999; Adhvaryu et al. 2010). This is believed to have added significantly to the duration of insolvency procedures in the country, which in turn induces firms to maintain suboptimal sizes. Related items of the Indian labor laws include the "service-rules" provisions of the Industrial Employment Act of 1946 and the provisions of the Contract Labor Act of 1970. The Industrial Employment Act requires defining job content, employee status, and area of work by state law or by collective agreement, after which changes would not be made without all workers' consent.[3] This has made it difficult for businesses "to shift workers not only between plants and locations, but also between different jobs in the same plant" (Zagha 1999).

To circumvent the restrictions, Indian businesses may resort to contract workers per the provision of the Contract Labor Act. However, this law also gives state governments the right to abolish contract labor in any industry in any part of the state. In states where recourse to contract labor has been more restricted as a result, the only ways of maintaining employment flexibility are to keep employment below the regulation threshold level of employees or to contract out jobs.

III. Data and Measurements

Survey Data Sources

We draw our firm-level data from the World Bank surveys on the two countries' investment climate. For 2000 to 2002, the surveys are similar in sample design and survey instruments. However, some differences remain. The India survey covered 1,860 manufacturing

[3] This applies to establishments with more than 100 employees. Zagha (1999) notes that some states have made the provisions mandatory to firms with 50 or more workers while other states have abolished the size limit altogether.

establishments, sampled from the top 40 industrial cities in the country, which were selected from 12 of the largest 15 states by picking the largest three or four industrial centers from each state. These 12 states were Andhra Pradesh, Delhi, Gujarat, Karnataka, Kerala, Haryana, Maharashtra, Madhya Pradesh, Punjab, Tamil Nadu, Uttar Pradesh, and West Bengal. These states account for more than 90 percent of India's industrial GDP while the three or four cities covered in each state accounted for the bulk of manufacturing outputs of their respective states. In each city, samples were drawn from the population of firms with more than 10 workers and in the main exporting or import competing manufacturing industries.[4] The total sample was allocated among states in proportion to a state's share in the national employment total of the eight industries. The systematic sampling rule sets an establishment's probability of selection proportional to the establishment's number of employees.

In the China survey, 2,400 enterprises were sampled from 18 cities considered to be representative of five regions. The cities include Benxi, Dalian, Changchun, and Haerbin (northeast); Hangzhou, Jiangmen, Shenzhen, and Wenzhou (coastal); Changsha, Nanchang, Wuhan, and Zhenzhou (central); Guiyang, Chongqing, Kunming, and Nanning (southwest); and Langzhou and Xi'an (northwest). Each of these cities was allotted a sample size of either 100 or 150 firms. These firms were then randomly drawn from an electronic database of firms from the list of industries. Unlike the India survey, the China survey covered firms from manufacturing and service industries.[5] The sampling frame in China was restricted to businesses that had an employment size more than 20 workers for manufacturing and 15 employees for service industries.

To ensure comparability, we select only manufacturing firms drawn from the industries covered in both the India and the China surveys.[6] In addition, while Indian firms are largely all private firms, many Chinese firms in our sample are state owned. Many commentators suggest that China's growth is largely due to the emergence of private firms. The share of private firms is indeed rising rapidly in China and has surpassed that of state-owned enterprises (SOEs) in its economic share. In 2000 and 2005, the share of state-owned employers account for only 32 percent and 24 percent of total employment, respectively. To make the sample as comparable as possible, in this paper we only keep the subset of private firms in China. Our final sample comprises 1,164 firms in China and 1,597 firms in India. The distribution of these by industry is shown in table 1.

Measuring Productivity and Growth

We aim to understand how labor regulation, skills and economic complexity explains the China–India gap in economic performance. For the micro counterpart to GDP per capita, we opt to use TFP to measure firm performance. The reason is that it is perhaps the best firm-level link to macro performance. Indeed, TFP has been shown to be a major source of output growth (Solow

[4] The industries are textiles, garments and leather goods, household electronics, electrical equipment and parts, auto and parts, food processing, chemicals and pharmaceuticals, and metallurgical products and tools.

[5] The manufacturing industries include garments and leather goods, household electronics, electrical equipment and parts, auto and parts, food processing, chemicals and pharmaceuticals, metallurgical products and tools, and transport equipment.

[6] That is, we have excluded textiles producers from the India sample and all service sector establishments and producers of transport equipment from the China sample.

1957; Jorgenson and Griliches 1967). Moreover, TFP levels are highly correlated with income per capita (Islam 1995; Hall and Jones 1999). In a survey of economic growth, Helpman (2004, p. 33) states, "There is convincing evidence that total factor productivity plays a major role in accounting for the observed cross-country variations in income per worker and patterns of economic growth. We therefore need to understand what drives the differences in total factor productivity." For this paper, we therefore focus on understanding the TFP differences between the two countries. Our TFP measure is closely correlated with log labor productivity (i.e., value added per employee), with a correlation coefficient of 0.61. Still, we have tried using log labor productivity as an alternative measure, and the results are robust qualitatively.

We estimate TFP for each of the seven industries listed in table 1. We assume that value added is Cobb-Douglas in capital services and labor input in each industry. Value added, V_{ijt}, is measured in constant U.S. dollars, where *i, j,* and *t* are firm, industry, and year subscripts, respectively. We proxy capital stock, K_{ijt}, by the constant dollar book value of fixed assets at the end of the fiscal year. Labor input, L_{ijt}, is measured by the average number of employees during a fiscal year. We estimate TFP as the residual (including the fixed effects) using the fixed effects specification (since we have three years of data for each firm).

A major concern is that productivity is a state variable that influences input choices: inherently more productive firms could employ more resources. Consistent estimates of the production-function parameters can, therefore, not be obtained by applying ordinary least squares (OLS) (or fixed effects).[7] To address this problem, we use the Levinsohn-Petrin (LP) estimator (Levinsohn and Petrin 2003), which addresses the simultaneity concern. Because the LP approach is more general than the fixed effects approach—which imposes time-invariant productivity—and directly deals with the simultaneity issue, we shall mainly rely on the LP productivity measure. However, we note that the correlation between the LP (tfpLP) and the fixed effects productivity is quite high: 0.73. In some sensitivity checks, we also use log labor productivity (measured as log value added per employees [logLP]) as our productivity measure. The correlation of tfpLP and logLP is quite high at 0.61.

We use value added as our output measure since the material input is the only non-state input that we can use to control for nonobservables. As it turns out, in some firms, the reported sales and purchase figures lead to negative value added due, perhaps, to measurement errors and to the existence of inefficient or distressed firms, as well as young firms suffering losses for future profits. While a natural thing to do may be to discard these as invalid entries, that could lead to a bias in our estimates of China–India performance gaps; we would have to drop more Indian firms than Chinese firms from the survey samples. We therefore drop 7.7 percent of firms on the bottom end of the distribution of value added per employees from each country sample in

[7] The main references on this problem and proposed solutions are Olley and Pakes (1996) and Levinsohn and Petrin (2003). See also Ackerberg, Caves, and Fraser (2006) for a critique of the Levinsohn-Petrin estimator we have used here, and see Wooldridge (2005) for the interpretation in a system equation framework. Ackerberg, Caves, and Fraser (2006) use the same invertibility condition as Levinsohn and Petrin (2003) but only a subset of the moments proposed by LP for estimation (Petrin and Sivadasan 2006). The criticisms of Ackerberg and Caves (2003) would be important when the variable input (labor) is a deterministic function of the state variable (say capital) and the proxy variable (material here) (Wooldridge 2005). To check this possibility, we regress log(labor) onto log(capital) and log(material) for each industry, and the R squares are around 0.6 to 0.8, far from being deterministic, so we are not worried about the Ackerberg and Caves criticism of the LP procedure in our context.

estimating the production function.[8] To the extent that the dropped Chinese firms are more efficient than Indian firms, our estimates would under-estimate China's advantage. But we believe the difference should be minor because both sets of firms are the worst performers.

China has a significant edge in productivity level (see table 2, and also Figure 2 for the full TFP distribution). Based on the median TFP, the China sample's premium is 1.27, which means that the median TFP for the China sample is 256 percent more productive than the India sample.[9] The mean advantage is slightly smaller, 120 log points. Chinese firms' mean TFP growth is higher than Indian firms' (3.6 percent for China and 2.9 percent for India), but their differences are statistically insignificant. Given the dramatic difference in TFP but no significant difference in TFP growth, we focus on TFP but not its growth here.

Measuring Skills

The average level of skills in a locality may matter for productivity of local firms for several reasons. It makes hiring qualified staff members easier and, therefore, reduces or eliminates the skill bottlenecks for local firms. Moreover, human capital externality at the local level might also increase the productivity of individual firms (Lucas 1988). Finally, if product quality is determined by the probability of not making mistakes by each staff, the level of production efficiency would depend on the distribution of skills for all staffs (Kremer 1993). Finally, the availability of local skills may have spillover effects through learning incentives: better skills of one staff would induce the other staff to acquire more human capital so that the return of investment in human capital would be higher.

The picture that emerges from comparing conventional indicators of skills between the two countries gives clear advantage for china. China has the advantage on adult literacy and school enrollment rates (including those for tertiary education). In 2003, India's adult literacy rate stood at 68 percent while China's was 95 percent (Deutsche Bank 2005). The tertiary enrollment rates for 2003 were 11 percent for India and 13 percent for China (Bardhan 2006). Since we do not have the schooling measure at the firm level, we proxy employee education by *the proportion of workers that regularly use computers while on the jobs.*

Our proxy indicates that Chinese firms have a slight edge, consistent with previous discussion of China advantage based on macro statistics (Deutsche Bank 2005; Bardhan 2006). On average, 22.2 percent of Chinese workers use computers regularly on the job, as compared to 16.7 percent of Indian workers. The median difference is 3 percentage points and statistically significant. Chinese employees are, therefore, more skilled than Indian ones.[10] There is some indication that local human capital level in India is related to labor regulation. Besley and Burgess (2004) classify Indian states into pro-labor (here for simplicity also include "neutral" states) and pro-

[8] The 7.7 percent city cut-off point ensures that all Indian firms with positive value added are included, but this means that some Chinese firms had to be dropped even when they had positive value added.

[9] We have tested the statistical significance of the difference in TFP between China and India, and it's significant at the 1 percent level.

[10] A caveat is that our proxy may capture not just skills, but also other things such as the spread of IT or new technologies. So, while we conveniently refer to this proxy as an indicator of skills, it can be interpreted as the penetration of IT as well.

employer states. The average of this skill proxy is much higher in pro-employer states than in pro-labor states: 0.193 versus 0.146.

Measuring Economic complexity

Economic complexity—that ability to produce sophisticated and diverse ideas and products--has been recently shown to be very important in understanding cross-country differences in growth (Hidalgo and Hausman 2009). In particular, Hidalgo and Hausman find that their national level measure of economic complexity is strongly associated with labor input quality, GDP per capita, GDP growth, and new varieties of export products. Similarly, Hausman, Hwang and Rodrik (2007) find that the level of sophistication of a country's export is a strong predictor of its subsequent growth. Theoretically, Rosenstein-Rodan (1943), Hirschman (1958), and Matsuyama (1992) all argue that it matters what types of products country produces because industrialization creates externalities that lead to accelerated growth. In similar spirits, Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1992) argue for the importance of technology in economic growth. Economic complexity to a great extent is similar to economy of agglomeration in that when firms with similarities congregate together, there is a positive spillover among them. There is one subtle difference in that economic complexity also entails the notion that there is an extra kick in spillover when capacity- or idea-sophisticated firms are located together.

At the city level, we do not have a good proxy of technological complexity except the share of firms that are large, that is, *the proportion of firms with more than 50 employees* in a city. The share of large firms in a city captures our notion of economic complexity to the extent that large firms are more technologically complex, produce more sophisticated ideas and products, and use better-skilled workers. An additional way that the share of large firms matters for local productivity is through the complementarity of capacity and ideas (Hidalgo and Hausman 2009). Imagine that large firms have higher capacity of different kinds, more large firms in a city implies the existence of sophisticated capacities in different firms. Since technogically more complex countries are more likely to export new varieties (Hidalgo and Hausman 2009), this suggests that capacity leads to more new ideas. Therefore, a firm located in a city with more sophisticated large firms should benefit more from external spillover of local capacity, such as through personnel turnover, the floating of ideas in the air, copying of local firms' ideas, marginal innovations based on more sophisticated ideas of local firms, and so on.

(Need to put in citations in the references.)

By our measure of economic complexity, Chinese firms are thus much more complex than India firms. The median of the ratios of large firms is three to four times as large in the Chinese sample as in the Indian sample. There is indication that local economic complexity level in India is closely related to other measures of labor regulation. The average of this complexity proxy is much higher in pro-employer states than in pro-labor states: 0.275 versus 0.194.

Measuring Labor flexibility

Labor inflexibility likely reduces productivity through two effects, the relative price effects and the expropriation effect (Besley and Burgess 2004). The relative price effect implies that labor regulation increases the relative price of hiring laborers. It increases the adjustment costs for firms. When hit by adverse demand shocks, firms would optimally reduce their workforces. Firing inflexibility would delay or prevent such adjustments and, therefore, increase operating costs and reduce firm profitability. Labor regulation also increases the marginal cost of production, therefore lowering total output. The expropriation effect refers to the adverse dynamic effect of labor regulation. With heavy labor regulation, labor's bargaining power rises. This may create the hold-up problem for firms' investment—workers can expropriate part of the return once the capital is sunk. Anticipating this, *ex ante* firms may become reluctant to expand and, therefore, fail to capture the economy of scale otherwise possible. Moreover, firms may fail to adopt technologies that can benefit only large firms, therefore further blocking the channels for innovation and technology adoption.

Our proxy for economic complexity, the city share of firms that employ more than 50 employees, also acts as a proxy for labor flexibility in India. Indian states with more stringent labor regulations impose higher costs for firms exceeding the labor regulation thresholds, and firms in these states then would be more reluctant to grow beyond the threshold. Our proxy therefore acts as a good proxy for labor regulation in India. In the meantime, of course, it also represents the outcome in economic complexity in both countries. A complementary partial indicator of labor flexibility is the lagged firm size (regarding the number of employees). The much larger average firm size in China also implies more labor flexibility in China.

Table 3 suggests that the Chinese labor market is more flexible. The median proportion of large firms in China is almost four times that of India: 77 percent in China versus 20 percent in India. As another indication of more labor flexibility, Chinese firms are clearly much larger than Indian firms, both in value added and the number of employees. While the mean number of employees is only 88 in India, it is roughly 400 in China. The size distribution of firms is of course very skewed. But even in median, China is much larger—China's 134 versus India's 18. Figure 3 shows the kernel distribution of log size, and it is clear that China's size advantage shows up in the whole distribution. If measured in total value added (in millions of 1999 U.S. dollars), China's mean is 6 times as large (6.4 versus 1 million), China's median is almost 14 times as large. Chinese firms are also younger, and their median age is 8, 4 years younger than its Indian counterpart.

IV. Empirical Framework and Results

We now conduct multiple regression analyses to examine the significance of skills, economic complexity (due to labor regulation) and labor regulation in affecting firm-level productivity. We run cross-section regression as follows, along with some more restricted versions:

$$Y_{i,c} = \alpha_c + F'_{ic}\gamma + COMPLEXITY_{jc}\delta + SKILL_{jc}\theta + COMPLEXITY_{jc}SKILL_{jc}\beta + \varepsilon_{ic} \qquad (2)$$

Here F is a vector of firm characteristics, COMPLEXITY is the city share of large firms, and SKILL is city average of the share of employees that regularly use computers. Subscript i, j, and c index firm, city, and country, respectively. The firm characteristics consist of the log of firm age and of lagged number of employees. We allow for country-specific intercept, which would capture all country-specific factors, including culture, the political system, and centralized level of regulation. For simplicity, we allow common coefficients for firm characteristics. For COMPLEXITY and SKILL, we will try both common and country-specific effects. Allowing country-specific coefficients and the likelihood of indirect policy impacts is to pay heed to the advice of the diagnostic approach to growth (Hausman, Rodrik, and Velasco 2005; Rodrik 2007), which emphasizes country-specific impacts of policies, and the O-ring theory of development (Kremer 1993), which suggests that policies often have important indirect effects on other policies, and some bottlenecks may have especially pronounced indirect effects.

We shall explore whether there are interaction effects between them, that is, whether capacity or economic complexity and local human capital are complementary. This interaction term is motivated by the endogenous growth literature. In summarizing new stylized facts associated with growth, Jones and Romer (2009) suggests that fact number one is the increase in the extent of the market. This stylized fact has strong implication for our understanding of productivity. They suggest that it is useful to understand productivity with a simple formula: $y = m\,L^{\gamma}$, where y is productivity, m represent a factor that captures the effect of institution, human capital, and other accumulation process, while L represents a scale factor that captures that number of people inside and outside a firm whose ideas directly benefit the firm, and γ is the degree of returns to scale. Our SKILL here is captured by m, while COMPLEXITY captures the scale of the extent of sophisticated firms in the city that contributes to knowledge, management practices for this city (i.e., L in the simple formula). The interaction of SKILL and COMPLEXITY therefore captures the interaction between the level of human capital and the scale of the capacity network.

Since our key measures such as SKILLS are observed only once at the end of the sample period, to avoid exaggerating precision, we only use 2002 observations for our estimation. Thus, although we have panel data of three years for financial variables, the regression samples consist of the cross-sectional sample of the final year (2002). However, in estimating productivity, we have three years of data, and we made use of all those data to improve the reliability of the productivity measures. In all regressions, we control for industry fixed effects.

Since our key explanatory variables vary only at the city level, and their coefficients are our parameters of interest, we cluster the standard errors at the city level to account for within-city correlation of the error terms and to avoid overstating our estimation precision (Bertrand, Duflo and Mullainathan 2004). Finally, since TFP (and log labor productivity) have significant outliers, we winsorize them at the tail 1 percent level. Winsorizing at the tail 2 percent and 5 percent leads to qualitatively identical results.

Note that our key measures, COMPLEXITY and SKILLS, are averaged at the city level. While COMPLEXITY is naturally measured at the city level, SKILLS can be measured either at the city or the firm level. To measure skills at the city level is to avoid the endogeneity issue associated with using the firm-level skill measure, which is a choice variable for the firm. Our identifying assumption is that these city-level averages are good proxies for our theoretical construct, and there are no omitted variables that are correlated with them and determine productivity. This is of course strong identifying assumption. Thus, our results should be properly interpreted as correlation and only suggestive of the importance of our proxies. The faith about a variable becomes stronger only when it is also consistent with our priors, other documented evidence, and complementary evidence.

Base Specification

In base specification in Table 4, we assume common effects for SKILL and COMPLEXITY for both countries without interaction effects. We report two specification, one in which the dependent variables is log of per-employee value added and we control for log capital-labor ratio interacted with industry dummies, and the other in which the dependent variable is TFP using the Levinsohn-Petrin procedure. Since the qualitative results are quite similar, we focus our discussion on the TFP results.

Firm size is positive and significant. Increasing firm size by 10 percent is associated with a productivity increase of 4.4 percentage point. Since firm size tends to be larger under less stringent labor regulation, this is consistent with the notion that stringent labor regulations hurt productivity. China's advantage in firm size also puts it ahead in its race with India in productivity. Younger firms are more productive. This again favors China since Chinese firms are younger. The mean (median) Chinese firm age is 3.5 (4) years younger.

SKILL is positive and significant, thought only at the 10 percent level. Increasing the share of computer-using staff at the city level by 10 percent is associated with an increase in productivity by 4.8 percentage points. Thus on average, higher local human capital is helpful for firm productivity. China's advantage in SKILL explains partly China's productivity advantage.

COMPLEXITY is strongly positively associated with productivity. Increasing the share of large firms in a city by 10 percent is associated with increasing productivity by 11 percent. Since COMPLEXITY drops with labor regulation in India, this finding suggests that an important channel through which labor regulations in India hinder productivity is economic complexity and economics of agglomeration. Since China has a big advantage in COMPLEXITY, this also puts China a big step ahead in the productivity race with India.

Further Results

Since the result is on COMPLEXITY is particularly strong, it is useful to have a sense whether it is robust to alternative ways to measure economic complexity. So far we have measured COMPLEXITY as the city share of firms with more than 50 employees. This captures both economic complexity of firms (assuming large firms are economically more complex on average) and the stringency of labor regulation in India. We now alternatively measure COMPLEXITY as the city share of firms with more than 100 employees. We chose 100 since it is another natural cutoff for large firms, and in many Indian states labor regulations begin to become tight after employing more than 100 employees. The results using this alternative definition is reported in column (1) in table 5. Both SKILL and COMPLEXITY remain positive and highly statistically significant. The benefits of COMPLEXITY are reduced somewhat from 1.1 to 0.64, suggesting that the type of economic complexity associated with 50-100 employees are perhaps larger.

In column (2) of table 5, we explore the idea that economic complexity matters only when it crosses some threshold. This is a natural idea in economics of agglomeration. Only when sufficient amount of capacity are congregated together, there would be sufficient economy of scale in knowledge production and sufficient economy of scale for specialized (and sophisticated) inputs. (would be nice if we have some cites) To test this idea, we create two dummy variables--one indicating the top half and the other the bottom half in COMPLEXITY--and interact them with COMPLEXITY. We thus allow COMPLEXITY to have distinct effects for the top and the bottom half of its distribution. Our conjecture is confirmed. For the bottom half distribution of COMPLEXITY, economic complexity has not a trace of payoff. Only for its top half distribution, economic complexity has strong payoff.

In column (3) of Table 5, we explore whether economic complexity and local human capital are complementary. To this end, besides SKILL and COMPLEXITY, we add their interaction term. Indeed, now only SKILL*COMPLEXITY is positive and statistically significant. This implies that at the 10^{th} percentile of SKILL (around 0.10 in both India and China), COMPLEXITY has a coefficient of roughly zero. At the median and 90^{th} percentiles of SKILL in India, COMPLEXITY'S coefficients are 0.41 and 0.63. In contrast, COMPLEXITY's coefficients in the median and the 90^{th} percentile in China are 0.60 and 1.41. The payoffs are thus the most pronounced for the top human capital cities between China and India.

In column (4) of Table 5, we explore the same complemetarity idea, but allow COMPLEXITY to have different effects for its top and bottom distribution, including the interaction effects. Now, only SKILL* COMPLEXITY FOR ITS TOP HALF is positive and significant. So we find support for two ideas: economic complexity has payoff only after some threshold, and there is complementarity between economic complexity and local human capital.

In column (5) of Table 5, we test the robustness of our results with respect to outliers. Since median regression is known to be less sensitive to outliers, we run median regression with the same specification as in column (4). Our key result, a positive and significant interaction term between SKILL and COMPLEXITY remain the same, with a slightly smaller magnitude (dropping from 4.47 to 4.27) and a significant increase in estimation precision.

Omitting Other Business Environment Ingredients?

There might be other important business environment variables that are missing from the equation which accounts for an artificial correlation between our two key variables and productivity. To address this concern, we further control for two prominent suspects from the business environment literature: access to finance, and local infrastructure quality (Xu forthcoming).

There is a vast amount of literature that links financial development to growth (see Levine 1997 for a summary). After all, the development of financial infrastructure allows firms to expand without solely relying on internal saving, reducing transaction costs between firms, and increasing the scope for specialization of firms. We capture the firm-level access to formal finance by whether a firm has *overdraft facility*, which is also used in the previous literature to measure formal access to finance (Dollar, Hallward-Driemeier, and Mengistae 2005). The proportion of firms with bank overdraft facility is 26 percent in China and 59 percent in India (table 3). Thus, Indian firms do better than Chinese firms in having access to bank finance.

Good infrastructure (e.g., power supply) would reduce production and transaction costs for firms. For instance, in the case of power supply, a good public supply of power would reduce or eliminate the need for individual firms to produce power in house, thereby realizing the economy of scale associated with power production. It also reduces the complexity and the amount of external finance for starting a new firm. We measure (the lack of) quality of power supply as the city average of the share of a firm's sales lost due to power outage. On average, sample Indian firms report 9 percent in lost sales against 2 percent in the China sample (table 3). Thus, China is superior to India in power supply.

In column (6) of Table 5, we further control the average city share of firm-level access to overdraft facilities (as a proxy of access to finance), and the average city share of losses of sales due to power outage (as a proxy of infrastructure quality). Again, our key results, the positive and significant interaction term of SKILL and COMPLEXITY remains intact, though smaller in magnitude now (dropping from 4.47 in column (4) to 3.48 here).

Allowing for Country-Specific Policy Effects

Going a step further, Table 6 allows the business environment variables to have country-specific effects. The two key variables now interact with the two country dummies. Again, we run two specifications, one with log labor productivity as dependent variable (and controlling for log capital-labor ratio interacted with industry dummies), and the other with TFP as the dependent variable. The results on firm characteristics differ little from the previous table.

The key finding is that both SKILL and COMPLEXITY do not matter in India, but matter in China significantly. This is consistent with the notion, as specified earlier, that a locality has to cross a threshold in COMPLEXITY for economic complexity to yield fruits for productivity, and there needs to be reasonable amount of complexity for local human capital to be productivity-enhancing. This is a neat demonstration of divergent force at work: once you have complexity, human capital transforms into something much more productive; once you have human capital, economic complexity tends to develop. The magnitudes of both variables are also huge in China. Increasing either COMPLEXITY or SKILL by 10 percent would increases productivity by 14 percentage points.

We have also tried allowing for country-specific interaction terms for the two variables. But we do not find such interactions. Thus, within our specific two countries, we do not find further complementarity, and the previous complementarity mainly comes from the China-India comparison.

Accounting for the China–India Difference

In table 7, we examine the relative quantitative significance of the few variables of ours in determining the productivity gap between our India and China samples. We conduct several accounting exercises. Column (1) is based on the specifications with country-specific business environment coefficients (i.e., table 6), in which case the contribution of factor X is simply $X_{China}\beta_{X,China} - X_{India}\beta_{X,India}$, where X_{China} is country-specific mean of X. Column (2) is based on the common coefficient model without interaction, and column (3) is based on the common coefficient model with interaction. To have a sense of the reliability of the decomposition, we bootstrap the decomposition 500 times to obtain the standard errors of the effect for each factor.

The mean China–India difference in TFP is 120 log points. The three models lead to the following implications. First, labor regulation is clearly the most important factor behind the China-India difference if we count log firm size and COMPLEXITY as both largely related to it. For the country-specific coefficient model, size and COMPLEXITY account for close to all or more than all of the China-India difference in productivity. Second, local human capital matters importantly, especially when we allow country-specific coefficients, in which case it accounts for slightly less than half of the differential. Third, for the horse race between local human capital and economic complexity, the latter always win. Forth, the interaction between local human capital and economic complexity is hugely important, accounting for 60 percent of the productivity differential.

V. Further Evidence for Labor Distortion in India

A key claim so far is that tight labor regulations likely hindered India's productivity level, and we have tried to establish this claim by linking productivity level with two variables related to labor regulation. We now offer further evidence that Indian labor regulations caused distortions amongst (regulated) large Indian firms.[11]

Since Indian state governments impose more stringent regulations for firms above certain size thresholds, we should find distortions for firms whose sizes border on those thresholds. Therefore, productivity should have a discontinuous drop as a firm's labor size passes the particular thresholds. The intuition is that, since firing employees become more difficult (or impossible) only after the regulation threshold, employees in firms under the regulation regime (i.e., cross the threshold) would, thus, work less hard with more job security, which in turn reduce TFP. Since the Indian economy is decentralized at the state level, the threshold may differ across states—with the most common at 50 employees. Therefore, we expect Indian firms in a neighborhood to the right of the regulation threshold to have lower productivity—once we have controlled smooth trend between productivity and log firm size. The empirical specification is as follows:

$$TFP_{ijl} = \alpha_j + \beta_j \ln L_{ij} + \sum_l \delta_l D_{il} + \varepsilon_{ij} \quad , \tag{3}$$

where *i, j, and l* represents firm, industry, and labor size segment indicators. We allow for industry dummies and industry-specific continuous relationship with log labor. Labor size

[11] We are grateful to Bernard Yeung for pushing us to go in this direction.

categories include less than 15, 15–49, 50–59, and 50 and above. The omitted category is 0 to 15. Since the dummy variable of 50-60 capture the difference from the group of 50 and above (since the group of firms with 50-60 employees are covered by the 50+ dummy and the 50-60 dummy), a negative and significant coefficient for the 50-60 employee dummy would confirm our hypothesis that links productivity dip to labor regulation.

A minor note is in order. For china, since the below-15-employee group is too small, we also tried using below 25 as the base category in column (1) of Table 8. The qualitative results are similar, so we'll stick to the common base category of below-15-employee for both countries.

Our conjecture is confirmed (see columns (2) and (3) of Table 8). For the China sample, the industry-specific smooth size trend is sufficient to capture the size-productivity relationship, and the extra size dummies are all insignificant. So there is no productivity dip for the 50-60-employee neighborhood in China. In contrast, Relative to the base category of less than 15 employees (and net of the smooth size trend effect), large firms have on average a productivity advantage of 33 log points—this perhaps reflects uncontrolled for economy of scale. Yet relative to all large firms, the 50-60-employee firms have a net dip of 41 percentage points, a large effect, supporting our hypothesis that Indian firms experience a productivity dip right after the regulation threshold.

Two more pieces of evidence further highlight labor distortion in India. First, pro-employer states in India show a less dramatic productivity dip across the regulation threshold than in pro-labor states. Besley and Burgess (2004) show that Indian states have passed various amendments to the Industrial Disputes Act of 1947. Taking advantage of the decentralized nature of Indian states, they classify Indian states as pro-employer, neutral, and pro-labor, with pro-labor states offering stronger protection for employees against being fired. They find that pro-labor states have worse productivity and employment growth. Following this lead, we test whether the productivity dip in India should be higher for pro-labor states than for pro-employer states, with the difference due to more severe labor-shirking effects (or other effects associated with labor regulation). To implement, we first classify the firms in our sample into those belonging to either pro-employer or pro-labor states. Since we have only around 100 firms in the "neutral" category (i.e., no amendments to the central government's labor regulation), we combine this with the pro-labor category. Columns (4) and (5) of Table 8 reports the results. In support of our hypothesis, the productivity drop (relative to the 50+ group) at the 50-60 employee segment is 32 log points (not significant) for firms in the pro-employer states, but 53 log points (significant) for those in the pro-labor states.

The second piece of evidence stems from comparing the size distribution of the three samples, which are ranked from the most to the least labor flexible: China, pro-employer, and pro-labor Indian states. Since a stronger labor regulation around the thresholds implies extra labor adjustment costs, Indian firms, especially those in pro-labor states, would have incentives to avoid crossing the labor thresholds. We therefore expect significant dips in the share of firms in the 50–60 size category and a higher cumulative share of firms below 50 employees. Indeed, this is true (see table 9). For China, the trend in size density is smooth: 22 percent for the 15–49 group, 5.9 percent for 50–60, and 71.6 percent for the 61+ group. The cumulative share of (small) firms with 50 or fewer employees is 22 percent. For pro-employer (pro-labor) Indian states, the share of firms is 35 (41.4) percent for the 15–49 group, 6.3 (2.3) percent for 50–60, and 21.3 (17.4) percent for the 61+ group. The cumulative share of small firms is 72.4 (80.4) percent for pro-employer (pro-labor) states. In pro-labor (relative to pro-employer) Indian states, there are clearly a larger share of small firms, and a thinner layer of 50-60 employee firms, indicating a stronger tendency for pro-labor states to avoid labor regulation across the 50-employee threshold.

VI. Conclusion

In this paper, we aim to explain the China–India productivity difference through labor regulation and its consequence. We find that India has worse skills, smaller firms, and lower economic complexity. Skills and economic complexity on average have positive payoff, but the effects depend on economic context. Only when crossing some threshold would economic complexity has positive payoff, and the payoff is indeed amazingly large. We also find strong complementarity between skills (and thus human capital) and economic complexity. While skills and complexity have no effect on average in India, they have positive and huge payoff in China. The most important factor behind China's productivity advantage is its larger firm size and economic complexity, followed by its local human capital level. Our results thus point to strong increasing-return-to-scale-typed explanation for China-India difference in productivity, and suggest that labor regulation may be the ultimate explanation behind it. We also find direct evidence of labor distortion in India. Although in China we don't find a productivity dip around firms with 51–60 employees (after controlling for continuous trend), this pattern is found for Indian firms, especially in those pro-labor states. Pro-labor Indian states also feature lower share of large firms and share of firms immediately beyond the labor regulation threshold (e.g., 50-60 employees) than pro-employer states.

While the findings in this paper seems to be potentially important and exciting, it is important to point out the limitation of this research. Our key measures are subject to multiple explanations. For instance, while we interpret the share of large firms as indicating economic complexity, it is clearly better to have direct measures of local economic complexity, such as the number of distinct products that a city produce or export. The key insights emerged in this paper remain conjectures without further, more refined empirical proof.

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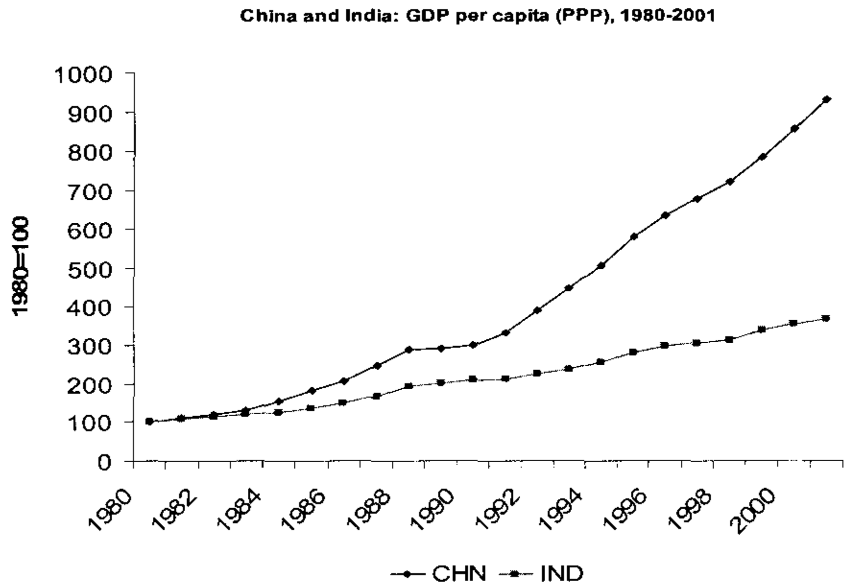
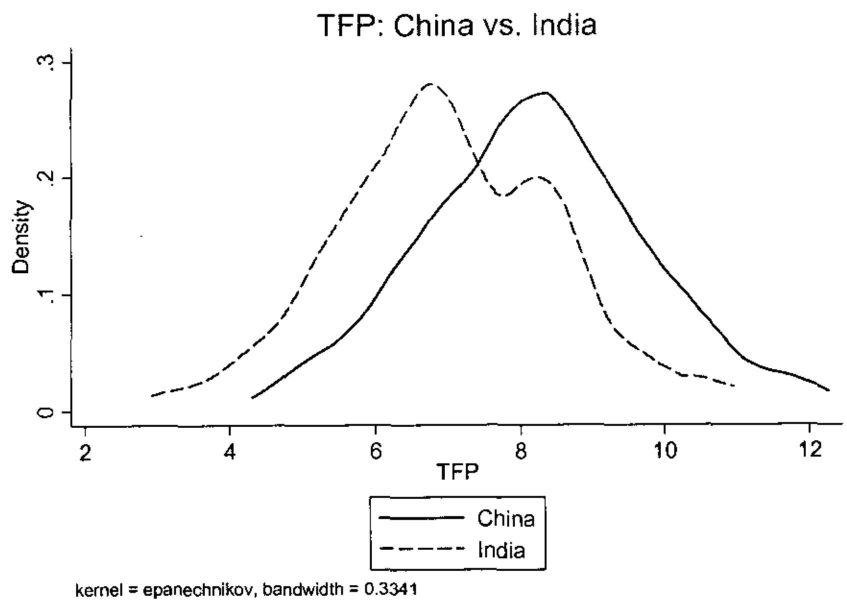
Figure 1. GDP per Capita Growth (in PPP) for China and India, 1980 to 2001



Source: World Bank, World Development Indicators.

Figure 2. Distribution of TFP for China and India



Note. Based on the Levionsohn-Petrin version of TFP.

Figure 3. Distribution of log(number of employees) for China and India

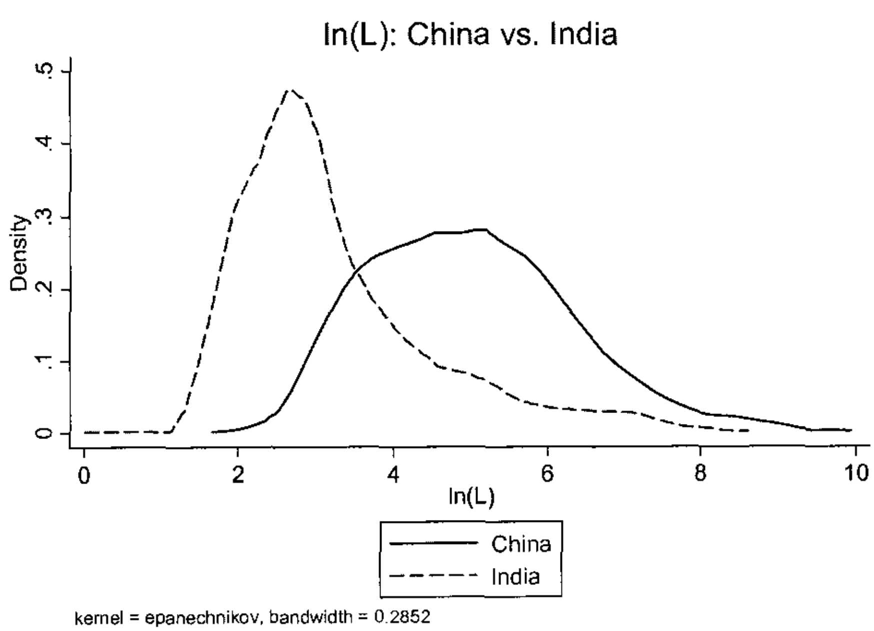


Table 1. Industry Distribution of Sample Firms

	China	India
Industry	Number of firms	Number of firms
Garments and leather products	279	336
Household electronics	54	129
Electrical equipment and parts	360	147
Auto and parts	252	245
Food processing	52	195
Chemicals and pharmaceuticals	70	384
Metallurgical products and tools	97	161
Total	1,164	1,597

Table 2. Differences in Performance and Firm Characteristics

	India					China				
	mean	sd	p10	p50	p90	mean	sd	p10	p50	p90
TFP based on Levinsohn-Petrin estimates, winsorized at 1 percent.	7.000	1.554	5.071	6.931	8.893	8.198	1.535	6.214	8.198	10.207
Ln(Value added per employee), winsorized at 1 percent.	7.820	1.197	6.325	7.932	9.267	8.502	1.225	6.878	8.513	10.145
TFPLP growth, winsorized at 1 percent.	0.029	0.496	-0.464	0.006	0.485	0.036	0.492	-0.523	0.045	0.590
Firm age	15.874	16.739	4.000	12.000	31.000	12.302	11.449	4.000	8.000	32.000
Value added (in million 1999 U.S. dollars)	1.008	7.546	0.007	0.052	0.856	6.389	37.331	0.050	0.689	11.347
Number of employees	88.132	292.02	7.000	18.000	150.00	398.18	989.98	28.000	134.50	819.00

Table 3. Differences in Firm Characteristics and the Business Environment

	India					China				
	mean	**sd**	**p10**	**p50**	**p90**	**mean**	**sd**	**p10**	**p50**	**p90**
City average share of firms with more than 50 employees	0.224	0.181	0.000	0.200	0.436	0.777	0.142	0.604	0.768	0.966
City average share of workers that regularly uses computer at work	0.167	0.050	0.091	0.176	0.217	0.222	0.088	0.109	0.211	0.363
City average of access to overdraft	0.560	0.205	0.176	0.588	0.775	0.300	0.107	0.163	0.264	0.531
City share of loss of sales due to power outage	0.090	0.049	0.039	0.090	0.127	0.020	0.009	0.008	0.018	0.036

Table 4. Business environment and firm performance: common coefficients

	Ln(value added per employee)	TFPlp
China dummy	-0.429***	-0.127
	(-4.790)	(-0.883)
$\ln(L_{t-1})$	0.134***	0.440***
	(7.042)	(20.111)
Ln(firm age)	-0.114**	-0.137***
	(-2.232)	(-2.751)
SKILL: city average of the share of employees that	0.533***	0.475*
regularly use computer	(3.030)	(1.915)
COMPLEXITY: Mean city share of large firms (i.e., L>50)	0.812*	1.114**
	(1.949)	(2.395)
lnk * industry dummies	yes	no
N obs.	2,381.	2,381.
Adjusted R2	0.366	0.622

Note. * statistically significant at 10 percent level; **, 5 percent; ***, 1 percent.
Standard errors, clustered at the city level, in parentheses.
Intercept not reported.

Table 5. Business environment and firm performance: further elaborations

	Large firms: 100+ employees	Different coeff for top and bottom city complexity	Interacting skill & complexity	Interacting skill & complexity, & two types of complexity	Median regressions	Adding other business environment indicators
SKILL:	0.968**	1.032**	-2.144*	-1.487	-2.085***	-0.836
	(2.136)	(2.240)	(-1.856)	(-1.310)	(-3.215)	(-0.829)
COMPLEXITY	0.637***		-0.519		0.132	
	(2.751)		(-1.635)		(0.571)	
COMPLEXITY for bottom half		0.038		-0.020		0.943
		(0.090)		(-0.024)		(1.087)
COMPLEXITY for top half		0.635***		-0.240		-0.026
		(2.858)		(-0.800)		(-0.080)
SKILL * COMPLEXITY			5.305***			
			(3.783)			
SKILL * COMPLEXITY for top half				4.473***	4.269***	3.480***
				(3.239)	(4.648)	(2.741)
SKILL * COMPLEXITY for bottom half				0.240	-0.621	-5.987
				(0.049)	(-0.399)	(-1.356)
also control for China dummies, ln(L1), ln(age)	Yes	Yes	Yes	Yes	Yes	Yes
city average access to overdraft facilities, city average of loss of share of sales due to power outage	No	No	No	No	Yes	Yes
N obs.	2,381	2,381	2,381	2,381	2,194	2,194
Adjusted R2	0.623	0.623	0.626	0.627		0.633

Note. * statistically significant at 10 percent level; **, 5 percent; ***, 1 percent.

Standard errors, clustered at the city level, in parentheses. Intercept not reported.

COMPLEXITY: city average of the share of firms that employ more than 50 employees.

SKILL: city average of the share of employees that regularly use computer.

Table 6. Business environment and firm performance:

Country specific coefficients

	Ln(value added per employee)	**TFPlp**
China dummy	-1.319***	-1.429***
	(-7.890)	(-7.820)
$\ln(Lt-1\ \ )$	0.130***	0.430***
	(6.712)	(19.273)
Ln(firm age)	-0.108**	-0.126**
	(-2.071)	(-2.501)
India * COMPLEXITY	0.224	0.015
	(1.364)	(0.063)
India * SKILL	-1.333	-1.408
	(-1.624)	(-1.609)
China * COMPLEXITY	1.017***	1.448***
	(4.706)	(5.584)
China * SKILL	1.422***	1.400***
	(3.654)	(3.542)
lnk * industry dummies	yes	no
N obs	2381	2381
Adjusted R2	0.373	0.630

Note. * statistically significant at 10 percent level; **, 5 percent; ***, 1 percent.

Standard errors, clustered at the city level, in parentheses.

Intercept not reported.

We have tried country-specific interaction terms, and do not found any.

COMPLEXITY: city average of the share of firms that employ more than 50 employees.

SKILL: city average of the share of employees that regularly use computer.

Table 7. Accounting for the TFP differential

Contribution of the following factors for $\Delta TPF_{china-india}$ =1.20	(1) Country-specific coefficient	(2) Common coeff., no interaction	(3) Common coeff., with intereaction
China dummy	-1.429***	-0.127	-0.112
	(-7.339)	(-1.296)	(-1.192)
$\ln(L_{t-1})$	0.757***	0.775***	0.754***
	(17.703)	(18.320)	(17.552)
Ln(firm age)	0.026***	0.028***	0.028***
	(3.491)	(3.865)	(3.549)
COMPLEXITY	1.121***	0.262***	-0.287**
	(5.568)	(3.084)	(-2.379)
SKILL	0.546***	0.062***	-0.118***
	(4.079)	(3.571)	(-3.163)
SKILL * COMPLEXITY			0.755***
			(5.771)

Note. *, statistically significant at 10 percent; **, 5 percent; ***, 1 percent.
Standard errors, in parentheses, are based on bootstrapping 200 times.
(1) Based on coefficients of Table 4. (2) Based on common coefficient model. (3) Based on common coefficient model with interaction term.

Table 8. Are there size distortoins?

	China	**China**	**India**	**Pro-business India**	**Pro-labor India**
Base	Less than 25	Less than 15	Less than 15	Less than 15	Less than 15
L: 25-49	-0.040				
	(-0.285)				
L: 15-49		-0.144	0.064	-0.093	0.176
		(-0.521)	(0.786)	(-0.655)	(1.630)
L: >=50	0.110	-0.001	0.327*	0.097	0.463*
	(0.740)	(-0.002)	(1.767)	(0.323)	(1.822)
L: 50-60	0.043	0.044	-0.408**	-0.324	-0.525*
	(0.306)	(0.313)	(-2.476)	(-1.406)	(-1.901)
intercept	4.943***	5.052***	5.360***	4.900***	5.917***
	(7.618)	(7.280)	(17.564)	(10.326)	(16.740)
N obs	1,143	1,143	1,427	619	732
Adjusted R2	0.554	0.554	0.564	0.581	0.531

Not reported are coefficients of industrial dummies, and lnL*industry dummies.

Table 9. Density Distribution of Firm Size: China, India pro-business, India pro-labor

	density			Cumulative density		
	China	Pro-business	Pro-Labor	China	Pro-business	Pro-Labor
Less than 15 employees	0.008	0.374	0.39	0.008	0.374	0.39
15-49 employees	0.216	0.35	0.414	0.224	0.724	0.804
50-60 employees	0.059	0.063	0.023	0.284	0.787	0.826
61+ employees	0.716	0.213	0.174	1	1	1