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Diagnosing Development Bottlenecks

China and India

Wei Li
Taye Mengistae
Lixin Colin Xu

The World Bank
Development Research Group
Finance and Private Sector Development Team
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Abstract

Although it had a a lower income level than India in 1980, China's 2006 per capita gross domestic product stands more than twice that of India's. This paper investigates the role of the business environment in explaining China's productivity advantage using recent firm-level survey data. The analysis finds that China has better infrastructure, more skilled workers, and more labor-hiring flexibility than India, but a worse access to finance and higher regulatory burden. Infrastructure appears to be a key constraint for India: it lags significantly behind China, yet it has important indirect effects for the effectiveness of labor flexibility. Labor flexibility is also likely a major constraint for India, as evident in the predominance of small firms, the importance of firm size in accounting for India's disadvantage in productivity, and the complementarity of proxies of labor flexibility with infrastructure and access to finance. Interestingly, regulatory uncertainty has adverse effects in India but not in China. The empirical analysis suggests that it is important to consider country-specific growth bottlenecks and the indirect effects of policy reforms.

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The author may be contacted at lxu1@worldbank.org.

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Wei Li Taye Mengistae Lixin Colin Xu

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I. Introduction

In 1980, China and India, the two most populous countries on earth, were both very poor. India had a nontrivial lead in per capita GDP; per capita GDP was $2.38 per calendar day, nearly one dollar more than in China.[2] In 1980, China was already more than two years into its gradual economic reforms, whereas India did not embark on economic liberalization until 1991. Economic liberalization in both countries was followed by accelerated economic development. By 2000, daily GDP per capita had risen to $7.30 in China and to $4.71 in India, giving China a lead of $2.59. By 2008, China's per capita GDP (measured using the PPP exchange rate and 2005 international dollar) stood at $5,515 per year, or $15.11 per calendar day, and India's per capita GDP at $2,721 per year or $7.45 per day. While both China and India are success stories in economic development, the performance gap between China and India deserves attention. With only two countries to compare, macro data are of little use since time-series variations alone may not offer sufficient degrees of freedom for statistical inference. Using firm-level data, however, we can transcend the constraint of macro data by examining cross sectional, as well as temporal, variations. We can link firm productivity—presumably the most important factor contributing to income per capita (Islam 1995; Hall and Jones 1999)—to city-level business environment, such as skills, infrastructure, labor regulation, regulation burden, and access to finance. In particular, we recognize that constraints to economic development tend to be location-specific. Following the diagnostic approach to growth (Hausman et al. 2005), we employ firm level data to identify key constraints to development (Lin and Monga 2010). Our presumption is that, even within a country, there are sufficient variations in the city-level aggregates that we can use to gauge the effects of the policy and business environment on firm-level productivity.

Our firm-level data are from comparable samples of manufacturing businesses in the two countries, namely, 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 covering 15 provinces and 5 geographic regions. In addition to collecting annual data on each sample firm's characteristics, financial accounts and operations between 2000 and 2002, the survey also collected data on the local business and policy environment that each sample firm faced

[2] We calculate daily income based on GDP per capita, measured using purchasing-power-parity (PPP) exchange rate and 2005 constant international dollar, as reported in the 2010 World Development Indicators published by the World Bank. Per capita GDP in China was $1.43 per calendar day in 1980.

between 2000 and 2002. The available data allow us to construct indicators measuring the quality of firms' external environment at the city level along these dimensions: infrastructure, labor market practices, labor skills, regulatory burden, and access to bank finance.

Our empirical findings confirm that by the early 2000s, Chinese firms already had a sizable and statistically significant lead in total factor productivity (TFP) relative to their Indian counterparts. We also find that the China-India productivity gap is attributable to some environmental factors. Not surprisingly, we find that workers' ability to use computers matters. Chinese firms employ more skilled labor than Indian firms, as measured by the percent of workers who use computers in a city. A greater use of labor with a higher level of skills is positively and significantly correlated with Chinese firms' TFP, but not with Indian firms' TFP. China's labor skill advantage explains a nontrivial part of China's productivity advantage at the firm level.

Chinese firms have significantly less access to short-term bank financing than Indian firms, irrespective of firm size. On average, access to short-term finance in neither country is significantly related to productivity. In India, we also identify an import indirect effect from easier access to short-term bank loans: it improves the return to labor flexibility. The role played by infrastructure (using power supply reliability as a proxy) is complex. On average, it does not directly affect productivity in either country. However, it has important indirect effects in India: a better local infrastructure allows firms to benefit more from a more flexible labor market.

Labor markets are more flexible in China than in India. First, nonpermanent workers compose a larger fraction of employment among firms in China than in India. Moreover, Indian laws severely hamper firms' ability to hire and fire workers once their employee counts reach certain thresholds (such as 50 employees), leading to the predominance of small firms in the Indian economy. Indeed, around 80 percent of sampled Indian firms employ fewer than 50 employees, while only around 20 percent of Chinese sample firms are this small. We find that the share of nonpermanent workers has a greater productivity advantage in India than in China, suggesting that labor flexibility is a stronger constraint in India. Moreover, we find that the share of nonpermanent workers and the share of large firms have important indirect effects by causing the return of access to bank finance and the return to infrastructure to increase in India.

The paper is related to three strands of literature. The first is the literature on the China–India comparison in economic performance. 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 firm-level 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. Our paper differs in that we focus on policy and environmental factors that may explain India's disadvantage in performance and find that labor regulations and infrastructure seem to be particularly relevant.

The second related literature links Indian economic performance with its labor market flexibility. Besley and Burgess (2004) use state-level panel data from India to investigate the impact of labor regulation on state economic performance and find that pro-labor regulations hinder economic performance. Amin (2009a, b) find that cumbersome labor regulations in India lead to smaller firm sizes, more informality, and inefficient adoption of labor-saving computer technology. Aghion et al (2008) link the elimination of the system of industrial regulation with state-industry-level performance over time in India. They find the growth effects of de-licensing to be significantly stronger in states with pro-employer than in pro-employee labor regulations. World Bank (2010) argues that labor regulations in India encourage informality and dualism in India. We add firm-level evidence on the complementarity between labor flexibility, infrastructure and access to finance in India.

The third strand of related literature analyzes the impact of measurable business climate on firm performance. Since Stern (2002) argues for improving business climate and overcoming government failure as a strategy for development, the World Bank has conducted numerous investment climate surveys in developing countries.[3] The existing studies have tended to assume identical effects of business climate on firm performance across countries. Our results suggest that, consistent with Hausman et al. (2005) and Kremer (1993), it is critical to allow for heterogeneous policy effects, to recognize local variations in policies and policy implementations within the same country, to consider interactions among various elements of the business climate, and to identify country-specific bottlenecks in economic development.

[3]See Ayyagari, Demirguc-Kunt, and Maksimovic (2008), Dollar, Hallward-Driemeier, and Mengistae (2005), Cull and Xu (2005), Cai et al. (forthcoming), Harrison et al. (2011), Hallward-Driemeier, Wallsten, and Xu (2006) on the effects of business environment on firm performance. Xu (forthcoming) offers a comprehensive survey of this new literature.

II. Research Strategy, Data, and Preliminary Comparisons

We aim to understand how differences in business environments contribute to the gap in economic performance between China and India using firm-level data. Given the importance of productivity in income determination, we use total factor productivity (TFP) to measure firm 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 (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 focus on understanding the TFP differences at the firm level between the two countries. For robustness checks, we also used labor productivity, measured by value added per employee in logarithmic scale, as an alternative dependent variable and we found similar results. In our data, TFP measures are closely correlated with labor productivity, with a statistically significant correlation coefficient of 0.61.

We proceed in three steps. First, we estimate total factor productivity for each firm in our sample. We then use available data to construct proxies for known business environmental factors that affect firms. At the last step, we estimate the effects of the proxies of the business environment on firm productivity using regression analysis. Our presumption is that even firms in the same country face different business environments at the local level. A caveat is that our results are only as representative as our sample. For example, our data do not reveal policy impacts on firm entry and exits. Also, because our data cover only manufacturing firms, our results do not apply to nonmanufacturing sectors. Finally, our sample does not contain what some view as the most productive sector in India—the software industry—which may bias our estimates and overstate China's productivity advantage.

Data

We draw our firm-level data from World Bank surveys on the two countries' investment climate in 2003. The two surveys are similar in sample design and survey instruments. However, some differences remain. The India survey covered 1,860 manufacturing establishments, sampled from the largest 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 one of the eight 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 in 15 provinces considered to be representative of China five geographic divisions. The cities include in the northeastern region, Benxi and Dalian (Liaoning Province), Changchun (Jilin), and Harbin (Heilongjiang); in the coastal region, Hangzhou and Wenzhou (Zhejiang), Jiangmen and Shenzhen (Guangdong); in the central region, Changsha (Hunan), Nanchang (Jiangxi), Wuhan (Hubei), and Zhengzhou (Henan); in the southeastern region, Guiyang (Guizhou), Chongqing (Sichuan), Kunming (Yunnan), and Nanning (Guangxi); and in the northwestern region, Lanzhou (Gansu) and Xi'an (Shaanxi). The total GDP of these provinces accounted for almost exactly half of the national GDP in 2007.[5] Each of the selected cities was allotted a sample size of either 100 or 150 firms. These firms were then randomly drawn from an electronic database of firms. Unlike the India survey, the China survey sampled firms from manufacturing and service industries.[6] The sample 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.[7] In addition, while Indian firms are largely all private firms, some Chinese firms in our sample are state owned. Many commentators suggest that

[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] National Bureau of Statistics, http://www.stats.gov.cn, accessed March 1, 2010.
[6] 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.
[7] As a result, we exclude textiles producers from the India sample and establishments in services and transport equipment sectors from the China sample.

China's growth is largely due to the emergence of private firms. Private firms have indeed grown more rapidly in China than state-owned enterprises (SOEs) to dominate job creation and production. In 2000 and 2005, the share of state-owned employers account for only 32 percent and 24 percent of total employment. To make the sample as comparable as possible, in this paper we keep only private firms in the China sample. Our final sample comprises 1,164 private firms in China and 1,597 firms in India. The distribution of these by industry is shown in table 1.

Productivity Estimation

While for our later regressions we shall only use one year of data due to the lack of variations for our key variables, for estimation of productivity we use three years of panel data. We assume that the value added, V_{ijt}, in firm i of industry j in year t, can be expressed by the following Cobb-Douglas production function,

$$\ln V_{ijt} = \gamma_j^K \ln K_{ijt} + \gamma_j^L \ln L_{ijt} + \eta_{ijt} \qquad (1)$$

where K_{ijt} is firm i's capital stock, measured by the book value of fixed assets at the end of the fiscal year t, L_{ijt} is labor input, measured by the average number of employees in fiscal year t, and η_{ijt} is the error term. In order to make cross-country comparison meaningful, V_{ijt} and K_{ijt}, are converted from units in local currencies to constant U.S. dollars using market exchange rates. Making use of three years of available data, we estimate TFP as the residual using the fixed-effects specification by assuming that $\eta_{ijt} = a_i + \xi_{ijt}$, where a_i measures firm-specific fixed effects on productivity.

A major concern with the fixed-effects specification is that productivity may have a component directly linked to a state variable, which in turn affects input choices: Inherently more productive firms would, under a competitive market mechanism or profit-oriented planners, employ more resources. Fixed-effects regressions may therefore produce inconsistent estimates of the production-function parameters.[8] To address this problem, we use the Levinsohn-Petrin (LP) estimator (Levinsohn and Petrin 2003). Because the LP approach is more general than the fixed-

[8] 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.

effects approach—which imposes time-invariant productivity—and directly deals with the simultaneity issue, we shall mainly rely on the LP productivity estimates in our comparative analysis. However, we note that the correlation between the LP (tfpLP) and the fixed-effects productivity is quite high: 0.73. In sensitivity checks, we also use log labor productivity (measured as log value added per employees) as our productivity measure. The correlation of TFP and log labor productivity is also quite high at 0.61.

We use value added as our output measure since material inputs are the non-state input that the Levinsohn-Petrin procedure uses to correct for simultaneity biases in estimating the Cobb-Douglas production function. As it turns out, in some firms, the reported sales are less than expenditures on intermediate inputs, resulting in negative value added. There are many reasons for this. Our sample period happens to cover a global recession after the bursting of the technology bubble. Some of our sample firms (in particular, exporters and firms that face import competition) could be experiencing recession induced distress. Our sample also includes young firms and some of the young firms could still be learning how to do business. There is also the possibility that some firms simply underreported their cash sales for the purpose of evading taxes.

It is tempting to simply discard firm-year observations with negative value-added. Doing so, however, could bias the comparative analysis of firm-level productivity between China and India since we would have to drop more Indian firms than Chinese firms from the survey samples. Instead, we drop 7.7 percent of firms on the bottom end of the distribution of value added per employees from each country's sample and use the remaining sample to estimate the production function of each industry.[9] 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.

Performance Differences

We present productivity estimates for the two countries in table 2. Relative to Indian firms, Chinese firms, on average, have a much higher level of TFP. The median firm's TFP in the China sample exceeds that in the India sample by 1.27 or 127 log points, which means that the median

[9] 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.

Chinese firm is 156 percent more productive than the median India sample.[10] Comparing sample means, Chinese firm's TFP advantage is a slightly smaller 120 log points. Chinese firms, on average, also have a positive, but statistically insignificant lead in TFP growth. The mean TFP growth rate in the China sample is 0.5 percentage points higher than in the India sample (3.6 percent for China and 2.9 percent for India), but this difference is not statistically significant. Given the dramatic difference in TFP levels and statistically insignificant difference in TFP growth rates, our analysis below will focus on comparing TFP levels.

Differences in Firm Characteristics

Chinese firms are much larger than Indian firms, whether we measure firm size by value added or by the number of employees. While the mean number of employees is only 88 in India, it is roughly 400 in China. The distribution of firm size measured by the number of employees in either the China sample or the India sample is skewed to the left. The median firm in the China sample employs 134 workers while the median firm in the Indian sample employs only 15 workers.[11] If measured in total value added (in millions of 1999 U.S. dollars), China's mean is 6 times as large (6.4 million versus 1 million), China's median is almost 14 times as large. Chinese firms also tend to be younger. The median firm in the China sample is 8 years old, 4 years younger than its Indian counterpart, a fact suggesting a more dynamic economy in China.

III. Measuring City-Level Business Environments

Stern (2002) notes that it is the "policy, institutional, and behavioral environment, both present and expected, that influences the returns, and risks, associated with investment" in a specific location. In other words, the business environment covers whatever external environment that affects the returns and risks faced by investors. Following this definition, we proxy the business environment, drawn from the literature on growth, on the following usual suspects: (a) quality of physical infrastructure, (b) skill level of local workforce, (c) access to finance, (d) flexibility in labor

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

[11] While by survey design, Indian firms are supposed to have more than 10 employees, and Chinese firms, more than 20 employees, the Indian sample has 25 percent of firms with less than or equal to 10 employees, and the Chinese sample has around 4 percent of firms with less than or equal to 20 employees. If we restrict the samples of both countries to have more than 20 employees, the median firm size for China is still much larger, 140 in comparison to 46.5 in India.

market, and (e) the deal environment.[12] Why and how does the business environment matter for firm performance?

Good *infrastructure* (e.g., roads and power) would reduce transaction, logistics and production costs for firms. For instance, in the case of power, a reliable 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 amount of capital needed for starting a new firm.

The 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 may increase the productivity of individual firms (Lucas 1988), and may also encourage entrepreneurship and innovations. Finally, if product quality is determined by the probability of not making mistakes in each task (the O-ring theory), the level of production efficiency would depend on the distribution of skills for all staffs (Kremer 1993).

We also include the ease with which firms can obtain short-term bank loans, our measure of access to *finance*, to be part of the determinants of firm productivity; following a vast amount of literature linking 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.

Labor inflexibility likely would reduce productivity (see Xu forthcoming for a summary of recent firm-level evidence). It increases the costs of adjusting a firm's scale of operation. 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. Anticipating this, firms may become reluctant to expand and, therefore, fail to capture the economy of scale otherwise possible. Indeed, Fallon (1987) and Fallon and Lucas (1993) find that strengthening labor regulation in India was associated with lower labor demand for large firms covered by the regulation, but not for small firms not covered by the regulations. Amin (2009a) find

[12] For more discussion, see, for example, Stern (2002) and Xu (forthcoming). There could be other important determinants; our selection is undoubtedly constrained by data availability. The China and India Enterprise Surveys are both non-standard—that is, they do not use the common survey instruments though they follow the common guidelines.

that cumbersome labor regulation in India leads to smaller firm sizes and more informality. Moreover, firms may fail to adopt technologies that can benefit only large firms, therefore further blocking the channels for innovation and technology adoption.

The deal environment faced by a firm matters in subtle ways to firm (Hallward-Driemeier et al. 2010). While the *de jure* regulations are the same within the same location or a country—say, the environment regulators should inspect a firm twice a year—the *de facto* regulatory burdens differ greatly among firms. In places where one can make deals and in places where the deal environment is more certain (i.e., the standard deviation of the regulatory burden is smaller), firms may have the option to circumvent cumbersome regulations and to do so with lower costs, and firms therefore should perform better.

While these factors might affect productivity, it is also conceivable that they may not be important in reality—it all depends on the economic environment (Hausman et al. 2005. Xu forthcoming). It is entirely possible that some economies are stuck with some bottlenecks elsewhere such that some of these factors may not matter after all (Kremer 1993). When technologies feature strong complementarity, a bottleneck such as skills may reduce the quality of inputs for the production process, directly lowering productivity. Moreover, the bottleneck may indirectly reduce incentives for workers to invest in human capital when the bottleneck reduces the return to human capital, further reducing skill improvements and productivity. Some bottlenecks then may keep the economy in a bad equilibrium for a long time. We shall let the data to inform us whether the business environment affects productivity. Below we discuss how we use available data to measure elements of the local business environment.

The quality of local physical infrastructure. While poor infrastructure is often cited as one of the key bottlenecks to growth in India (Pinto, Zahir, and Pang 2006), China has invested heavily on infrastructure. Since the mid-1990s, China has invested between 15-20 percent of its GDP on infrastructure. Infrastructure investment in India, in contrast, has averaged less than 7 percent of GDP. In absolute terms, China's infrastructure investment is about 8 times that of India's since the mid-1990s to the early 2000s (Ahya and Xie 2004).[13] Within the category of infrastructure, studies have

[13] A reason for the gap is that "a fiscal deficit of about 10 percent of GDP makes it hard for the India government to invest adequately in public infrastructure. The Chinese fiscal deficit is much lower (about 2 percent) and their tax-GDP ratio (at about 20 percent) is much higher, which along with larger household and corporate savings and foreign investment has made it possible for the massive investment in infrastructure" (Bardhan 2006, p. 8-9).

focused in particular on expensive and unreliable power supply as a source of development bottleneck in India (World Bank 2004). In China, reliability of power supply has also been a concern.

We therefore proxy for the quality of physical infrastructure that a firm faces in the city where it is located by the city average of the *negative* of the proportion of annual sales lost due to power outages that other businesses in the city report in the World Bank surveys. By excluding the firm's own report, we hope to minimize simultaneity biases caused by a likely reverse causation where a more productive firm is better equipped to deal with power outages, by, for example, investing in onsite power generating capacity. On average, sample Indian firms report 9 percent in lost sales against 2 percent in the China sample (table 3). The median difference is also 7 percent and statistically significant. Thus, China leads India in the quality of power supply.[14]

An alternative measure of power supply is the city share of firms having their own generators, which is also available from the data set. Using own generators is obviously a more expensive way to supply electricity for normal operations. In general, own generating capacity is often used as a source of emergency backup power. It would be more costly to rely on it for normal usage, and would require more capital expenditure to scale up when the firm expands production. In addition, a firm that uses continuous production processes would find any disruption in power supply unacceptable and would therefore invest in onsite emergency power even if external power supply is deemed reliable. The installation of emergency generating capacity by firms may not be a clean indicator of poor reliability of power supply from the grid. It is unfortunate that the surveys did not make a distinction between investing in own generating capacity as a substitute for electricity supply from the grid or as an emergency backup in the event that power transmission from the grid is interrupted

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[14] Some argue that roads (quantity and quality) are a better measure of infrastructure. We do not have city-level measures of road quantity and quality. However, the significant advantage of China in infrastructure should hold up if we instead rely on road measures. According to Postigo (2008), China has approximately 40,000 km of expressways, while India has only 300 km. Business perception of road quality is 4.6 (out of the 1–7 scale, with 1 being the worst and 7 being the best) in China, significantly higher than in India (3.0). The disadvantage of India is also reflected in its input: investment in road infrastructure accounts for 0.5 percent of India's GDP, but 3.5 percent in China. Moreover, the majority of roads are built in the countryside in India while most roads in China are for an expressway. India does have more total mileage in terms of road networks, but these are largely low-quality rural roads. Since all of our sample firms are located in cities, and what are relevant for them are largely high-quality expressways and paved ways, we're confident that China's advantage in infrastructure would be even more dramatic than as measured by power reliability.

by, for instance, increment weather. As a result, we do not find the variable measuring the share of firms having own generators a convincing measure of power supply reliability.[15]

***Skill level of local workforce*.** The picture that emerges from comparing conventional indicators of labor force skills between the two countries is rather mixed. China has the advantage on adult literacy and school enrollment rates (including those for tertiary education), but some believe India has more qualified engineers (Deutsche Bank 2005). 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 the surveys did not ask firms to report information on education attainments of their workers, we construct a proxy of the skill level of local workers that each firm faces in the city where it is located by the city average proportion of workers who regularly use computers at work as reported by other firms located in the same city. We exclude the firm's own report in order to minimize simultaneity biases caused by a likely reverse causation where more productive firms are able to hire more skilled workers. Our proxy indicates that Chinese firms have a slight edge. 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. A caveat is that our proxy may capture not just the skill level of the local labor force, but also other things such as the adoption of information technology (IT) in business. So, while we conveniently refer to this proxy as an indicator of skills, it can be interpreted as the penetration of IT as well.

***Access to finance*.** Since both countries share a basic feature of their financial system--a high level of government ownership of the banking system and high levels of government intervention (Cull and Xu 2000 and 2003; Dobson 2006; Bardhan 2006)--how much each country's financial system contributes to firm-level performance remains to be seen. We capture the firm-level access to short-term formal finance by whether a firm has an *overdraft facility* from its banks, which is also used in the previous literature to measure formal access to finance (Dollar, Hallward-Driemeier, and Mengistae 2005). Our measure of the ease of access to short-term bank finance that a firm faces in the city where it is located is the city average proportion of all other firms in the same city that report having bank overdraft facility. By this measure, Indian firms report easier access to finance than their Chinese counterparts: 26 percent of Chinese firms vs. 59 percent of Indian firms report having

[15] We did robustness checks by using the share of firms having own generators as an explanatory variable. We found that the variable has little power in explaining cross-sectional variations in productivity.

an overdraft facility (table 3). We recognize that this variable does not capture well the ease with which firms can obtain external finance for long-term investment.[16]

***Labor market flexibility*.** In the past, both India and China have suffered from excessive government-directed resource allocation. Their recent impressive growth is widely considered a result of the restoration of market-based resources allocation (Li 1997; Lin, Cai, and Li 2003). A key market-oriented reform has been the introduction of labor market flexibility.

China started liberalizing the labor market from the mid-1980s and deepened the liberalization with ownership and labor-restructuring reforms from the late 1990s. The reforms have given Chinese firms more flexibility than Indian firms have in adjusting staffing to meet changing economic conditions and to take advantage of technological developments (Ahya and Xie 2004; Dong and Xu 2009). The immediate consequence of China's labor market reforms is that firms can hire temporary workers. Chinese firms have taken advantage of this flexibility by increasing the proportion of workers on temporary contracts.

In India, the existing labor codes require businesses that have more than a threshold of employees to seek permission from state governments for closing a business or downsizing. [17]Permissions are rarely granted (Sachs, Varshney, and Bajpai 1999). Moreover, the threshold differs across states since both central and state governments are empowered to act on legislations related to trade unions and labor disputes (Besley and Burgess 2004). This is believed to have added significantly to the duration of insolvency procedures in the country, forcing 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.[18] 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

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[16] We have examined the robustness of this result with respect to sectoral composition, and find that the conclusion remains largely the same.

[17] See also World Bank (2010) for details on labor regulation in India.

[18] 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.

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 or to contract out jobs. Variations in the strictness of the enforcement of labor laws in India seem to be highly correlated with the proportion of contract labor. Given the institutional background, it is not surprising that Clark and Wolcott (2003) and Bardhan (2006) also conjecture that labor market inflexibility could be one important reason behind China's advantage over India.

To measure the local labor market flexibility that a firm faces in the city where it is located, we use *the city average proportion of nonpermanent employees* in the workforce as reported by other firms in the same city. For an additional measure of local labor flexibility that a firm faces in the city where it is located, we compute *the city average proportion of all other firms in the same city with more than 50 employees*. Our second measure is constructed based on the principle of "revealed costs" of labor regulation: To the extent that labor regulation in a city is less onerous, more firms there should be willing to step over the labor regulation threshold. Finally, a firm's lagged size (e.g., the number of employees) also may partially reflect the results of labor regulation.[19] Table 3 suggests that the Chinese labor market is more flexible. Although the difference between the mean proportions of nonpermanent workers is minor, the median proportion in China is almost four times that of India. In terms of the city share of large firms, China is more than three times as high as India (78 versus 22 percent). Similarly, the median firm size in China is 134 employees, in sharp contrast to only 18 in India. This difference is even more remarkable considering that the median firm is 4 years younger in the China sample than in the Indian sample.

To measure the deal environment, an aspect of governance, we follow Hallward-Dreimeier et al. (2010). We construct two variables. The first captures the extent that deals can be done, and it is measured as the share of senior managers' time that is used in dealing with government regulators ("the average time cost"). Since managers choose how much time they are willing to spend to lobby regulators, they would choose to spend more time lobbying if the expected gains from lobbying exceed the opportunity cost of their time. A larger value of this variable may thus mean that managers expect a greater likelihood of success in influencing government regulators. Interpreted this way, this measure should have positive effect on firm-level performance. This is similar to what is found in China, in which firms spend money to wine and dine government officials and such

[19] We have checked that the qualitative results about these measures of labor flexibility is the same if we control for sectoral composition in a city.

expenditures are found to have private benefits to firms in some circumstances (Cai et al. forthcoming). Alternatively, this measures the average regulatory burden, which should have negative effects on firm performance.

The second variable is the standard deviation of the share of senior managers' time that is spent in dealing with government regulators in the same city ("deal uncertainty"). A larger value means that the deal environment is more arbitrary and less certain. We expect this variable to have a negative effect on firm performance. Indeed, based on the World Bank Enterprise Surveys of around 100 countries, Hallward-Dreimeier et al. (2010) find evidence that the average time cost has positive effects while deal uncertainty has a negative effect on firm performance. However, as we emphasized, policy effects may differ in specific contexts. For instance, the effects of regulatory burdens and uncertainty may depend on the organizational details of bureaucracy. When firms have to go through decentralized corruption—that is, when firms have to bribe multiple, decentralized government regulators, and each regulator has discretion to stop the deal—the effect of regulatory burden and arbitrariness may be more pronounced (Shleifer and Vishney 1993, Berkowitz and Li 2000). Many observers of corruption have viewed India's corruption and regulation as typical of a decentralized setup, while China as being typical of a centralized setup (Berkowitz and Li 2000, Sun and Johnson 2009). We therefore expect the effects of these two variables to be more pronounced in India than in China. Table 3 shows that China features both higher time costs and deal uncertainty. While Indian firms on average spent 14% of their senior managers' time on dealing with regulators, the corresponding number of China is 20%. There are significant more variations in deal uncertainty in China as well: the standard deviation of this time cost is 13% in India, but 17% in China.

To summarize, relative to India, China has a better infrastructure (as measured by the share of losses of sales due to power outage), uses more skilled labor, and has greater flexibility in labor market. In contrast, Indian firms have better accesses to short-term bank finance and lower regulatory time costs and deal uncertainty than Chinese firms.

IV. Empirical Results

We now conduct empirical analyses to examine the significance of these business environment factors in affecting firm-level productivity. We run cross-sectional regressions as follows, along with some more restricted versions:

$$Y_{icjn} = F_{in}'\gamma_n + E_{cn}'\delta_n + \sum_{g \neq k} E_{cng}E_{cnk}\mu_{ngk} + \alpha_n + \beta_j + \epsilon_{icjn} \qquad (2)$$

Here the dependent variable, Y_{icjn}, is the total factor productivity of firm i in city c, industry j and country n, $F_{in}^{'}$ is a row vector of firm i's characteristics that may affect productivity (such as firm age and firm size), and $E_{cn}^{'}$ is a row vector that captures the local business environment in city c and country n. We allow for country-specific effects, α_n, which would capture the productivity effects of country-specific factors, including culture and the political system. We also allow for industry-specific effects, β_j. We allow the effects of firm characteristics to differ by country.

For the business environment factors, we include two components. The first is the direct effects of local business environment, captured by the second term on the right hand side of (2). In the specification, we allow the direct effects to differ by country. The inclusion of this term follows the diagnostic approach to growth (Hausman, Rodrik, and Velasco 2005), which emphasizes country-specific impact of policies. The second component, captured by the third term in (2), includes interactions among the business environment variables. This is again paying heed to the diagnostic approach to growth, and more specifically, to the notion of country-specific bottlenecks (Kremer 1993). Policies often have important indirect effects on other policies, and some bottlenecks may have especially pronounced indirect effects. Those with important positive externality for other policies are likely binding constraints and should receive higher priority in the reform agenda. This literature also notes that it is often difficult to find the interaction effects, perhaps because most existing studies have relied on country-level data, which may not offer sufficient variations. Our investigation of the indirect effects of policies is, therefore, new to the diagnostic approach. We also allow for country-specific coefficients for the interaction terms so that the indirect effects of a policy reform are allowed to differ because of the difference in policy complementarity.

Since the business environment measures, $E_{cn}^{'}$, are observed only once at the end of the sample period, to avoid exaggerating estimation precision, we only use observations in year 2002 for our cross-sectional estimation. Thus, although we have panel data for three years for financial variables, the regression samples consist of the cross-sectional sample of the final year (2002). However, in estimating productivity, we made use of all available data from 2000 to 2002 to improve the reliability of the productivity measures. Since some of the explanatory variables vary only at the city level, we cluster the standard errors at the city level to account for within-city correlation of the error terms and to avoid overstating 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.

Variables measuring the local business environment that a firm faces are constructed using city level averages of survey responses from other firms in the same city,[20] an approach that is widely used (Dollar et al. 2005, 2006; Hallward-Driemeier et al. 2006; Xu forthcoming). By averaging the reports of other firms, we avoid an obvious type of endogeneity: The reported data may be the result of a choice made by the firm, and may, therefore, be related to its unobserved productivity. Our identifying assumption is that these city-level averages are good proxies for the business environment of firms and that they are not correlated with a firm's specific capability. To the extent that this assumption is true, our estimation of the business environment effects is consistent. For the correlations between the business environment variables, see the appendix.

This is a strong identifying assumption. It can be violated if a firm's location choice is related to the local business environment or when we have omitted city-level variables that are correlated with our city-level proxies of the local business environment. However, with cross-sectional data available and with multiple environmental variables, we do not have convincing exclusion restrictions. We do believe that our business environment measures capture many important facets of a city's business environment, and the issue of omitted city information is less serious than it seems because we also control for country dummies, which hold the level of economic, political and social development constant. Furthermore, we often use multiple proxies of some business environment factors such as labor flexibility, and robust results on each proxy would boost our confidence that our results are not badly influenced by endogeneity biases. Still, our results should be properly interpreted as suggestive of the importance of various business environmental factors in determining productivity. Confidence in our results becomes stronger when they are also consistent with our priors, other documented evidence, and complementary evidence.

In using city averages, we assume a strong city component in business environment. If true, we must observe city-level variations. To check this, we regress those key variables observed at the firm level onto all city dummies. The null hypothesis that all dummy variables have zero coefficients is rejected in every case at the 1 percent significance level. These results are not surprising given the substantial variations in policies, policy implementation and business practices in across large cities in both China and India. They are also consistent with recent literature. Hallward-Driemeier et al.

[20] We dropped an Indian city from our sample since the city has only one relevant observation.

(2010) and Hallward-Driemeier and Pritchett (2010) emphasize that policy implementation differs greatly across regions even though firms within a country face the same *de jure* institutions. They show evidence that de facto enforcement of policies differ greatly at the local level within a country, and de facto business environment may matter much more than de jure business environment. Since enforcement of policies tends to be decided at the city level, we measure our environmental variables at the city level.[21]

Results from the Baseline Specification

We first report the regression results from the most restricted, also the most common, baseline specification—all coefficients are assumed to be the same for the two countries, and there are no interactions among the business environment variables. This specification assumes homogeneous policy effects across the two countries. For comparison purposes, we report results when productivity is either measured by TFP or by log labor productivity. In the latter case, we also control for the interactions of industry dummies with log capital-labor ratio. Since the environmental variables are correlated with each other (Appendix table), we are concerned about the effects of multicollinearity when we include all of them in the regression. We therefore start by including them one by one in our regressions, and then include them all together to see if the results change much. Only one environmental variable, deal uncertainty, has different results between the one-by-one specification and the all-included specification. We present the results based on labor productivity in table 4, and those based on TFP in table 5.

Comparing the results in tables 4 and 5 reveals that we obtain qualitatively identical results whether we use labor productivity or TFP as the dependent variable. For this reason, our discussion below will focus on results in table 5 where we use TFP as the dependent variable. The three indicators of labor flexibility—the share of nonpermanent workers, the share of large firms, and lagged firm size—all have positive and statistically significant (or close to being so) coefficients.[22]

[21] Alternatively, we can measure it at the provincial or state level. However, measuring this way suffers from two problems. First, given that recent studies find enforcement matter a great deal, it is more appropriate to measure the business environment at the more decentralized city level. Second, given the state and province tend to have some policy formulation role, provincial measures of the environment may reflect better de jure policy environment. However, recent studies have shown convincingly that what matters tend to be de facto rather than de jure regulations (Hallward-Driemeier et al. 2010; Hallward-Driemeier and Pritchett 2010). Finally, we have more variations at the city than at the province/state level, and given the number of policy variables we examine, more degrees of freedom also provide a great practical advantage.

[22] It is important to point out, however, that some of our proxies for labor flexibility, such as firm size, may reflect other factors such as a legacy of earlier small and medium enterprise sector reservations, skills, and managerial control system. We thank Giovanna Prennushi for pointing this out.

Higher labor flexibility alone appears to put China in front in the productivity race. Of the China advantage in productivity (1.20), the China advantage in (lagged) firm size (1.76) explains (in the accounting sense) 62%; the share of large firms, 25%; the share of nonpermanent workers, 22%. Labor flexibility-related measures, therefore, account for roughly 110% of the China-India differential in productivity.

Younger firms are more productive. This also favors China since Chinese firms are younger. The mean Chinese firm age is 3.5 years younger, and this variable therefore account for about 3% of the productivity differential between China and India. Another factor that is positively and significantly related to productivity is the share of computer-using workers. Since China has a higher share of computer-using staff members (by 0.055), this variable explains about 5% of the productivity differential between China and India. In contrast, mean power reliability and the access to finance are not significantly related to productivity at 5 percent level. Consistently with Hallward-Dreimeier et al. (2010), managerial time cost has positive while deal uncertainty has negative effects on TFP. We thus directly use their interpretations. The positive effect of managerial time costs likely reflects the fact that, holding deal uncertainty constant, locations with higher managerial time costs likely have higher potential gains for firms to make deals with government regulators, and this may increase the chance of successes of business ventures. The negative effect of deal uncertainty, in contrast, reflects the fact that deal uncertainty increases transaction costs. Since China leads India in both managerial time cost and in deal uncertainty, the two effects are partially offsetting in explaining China's productivity lead. The next effect, evaluated using country means for both explanatory variables, is 0.088, which explains 7.3% of China's lead in TFP.

It is worth noting that the estimate of the coefficient on the China dummy is negative, offsetting the over-contribution of the environmental variables to the observed China-India productivity gap, by an economically and statistically significant 35%. This suggests that the regression model is likely misspecified. By forcing the productivity effects of the environmental variables to be the same between China and India, this specification may have overestimated the effects for China and underestimated the effects for India, letting the China dummy to compensate for the specification biases.

Allowing for Country-specific Environmental Effects

Going a step further, we now allow the business environment variables to have country-specific coefficients on TFP and present the regression results in table 6.[23] The reported coefficient for a particular variable in a country reflects the total effect of this variable on TFP in that country, and is therefore directly comparable for China and India.

The results on firm characteristics are interesting. Lagged firm size has a larger coefficient in China (0.46) than in India (0.39), suggesting that Chinese firms benefit more from economies of scale than Indian firms. This renders support to the notion that labor regulation is more damaging for large firms in India. Moreover, younger firms are more productive only in China. Since Chinese firms are on average 3.5 years younger than Indian firms, this finding suggests that the Chinese economy had been able to derive more benefits from growth and innovations.

Our physical infrastructure proxy, power quality, has statistically insignificant effect on TFP in China, but a negative and statistically significant effect on productivity in India. This strange result –-normally one expects that power quality should be positively correlated with productivity-- likely reflects a reverse causality: Infrastructure investment takes time to plan and complete. With only a decade in pursuing growth oriented policies, India was likely behind in infrastructure investment. Regions with higher growth might therefore have felt more acutely the constraints of power supply than other regions. This is not the case in China because China had invested aggressively in power generation capacity since the 1990s and China likely did not face binding capacity constraint in electricity in our sample period, a period of global economic recession and reduced demand for Chinese manufactures.

Similar to the results in table 5, estimates of the coefficient of the access to finance variable, city share of overdraft facility, are all positive, but not statistically significant for both countries. However, the previously found positive effects of the average share of computer-using staff members are no longer observed among Indian firms, but appear to have larger magnitude among China firms (1.63 here versus 1.17 in table 5). Thus, skills do have significant and much larger payoffs in China than in India, and the common effects specification in the previous table wrongly infer positive effects of skills in India.

The effects of the city-level labor flexibility measure, positive and significant in both countries, are now much bigger in India than in China. The coefficient of the share of nonpermanent

[23] Results based on log labor productivity are very similar.

workers is six times larger in India than in China (2.09 versus 0.33). Interestingly, the estimate of the coefficient of the share of large firms is statistically significant only in China. While the estimate of the coefficient for India is very small and insignificant (0.29), it is quite large for China at 1.05 and statistically highly significant. Labor flexibility may thus generate benefits beyond simple internal economies of scale, which are measured by the coefficient on lagged firm size. By removing the regulatory constraints on firm size, firms within a city grow larger and more firms enter. Each firm benefits from economies of agglomeration. Our estimates show Chinese firms benefit far more from economies of agglomeration than their Indian counterparts.

The estimates of the effects of managerial time costs and deal uncertainty in India are qualitatively identical to those in table 5. But the estimates of the effects in China have similar signs, but are not statistically significant. This suggests that deal environment is more important in India than in China. The more adverse effects of deal uncertainty in India are consistent with some economics and politics literature such as Shleifer and Vishney (1993) and Berkowitz and Li (2000). Sun and Johnson (2009) argues that decentralized corruption (i.e., many regulators can collect tolls for a certain business deal) commonly associated with India tends to pose more damaging effects on efficiency than centralized corruption, commonly associated with China.

Moving from the common-effects specification reported in table 5 to the country-specific effects specification reported in table 6 has resulted in much more informative inference about the differences in how environmental variables impact firm-level productivity in the two countries. The differences are economically and statistically significant. Interestingly, the China dummy is now positive and statistically insignificant once we allow country-specific effects in the specification. Our results thus suggest that the China-India difference in average productivity at the firm-level is attributable to the set of included environmental variables in the more flexible specification.

But the results also show that infrastructure and finance do not matter importantly in either country. Is this really so?

Allowing for Interactions among the Environmental Variables

Both China and India are countries with many significant distortions (Hsieh and Klenow 2009). Reforms that eliminate one distortion often have indirect welfare effects by loosening or aggravating the effect of other distortions. An empirical strategy to identify the importance of a specific policy would be to allow this policy to interact with other policies in the outcome function.

Even if a policy does not generate any direct effect on productivity, if its implementation makes other policies more effective in improving productivity,[24] it is desirable to have (Hausman et al. 2005).

Since our policy variables vary only at the city level and we have a limited number of cities in our sample, multicollinearity would be a serious problem if we were to incorporate all possible interactions among variables measuring local business environment. To adopt a parsimonious specification, we tried a full set of China- and India-specific interaction terms. None of the China-specific interaction terms are statistically significant at 5 percent level. For India, only two interaction terms are statistically significant. In Table 7, we present the results from a specification that includes only two of the statistically significant interactions for the India sample.

Before proceeding to discuss the other coefficients, we note that the China dummy is now positive and significant at 5 percent level. This implies that Chinese firms exhibit unobserved advantage that is not captured by our explanatory variables. However, we probably should not read too much into this unobservable-based advantage since once we deal with outlier issues later, the China dummy becomes statistically insignificant.

For India, our proxy of labor flexibility (including both the share of non-permanent workers and the share of large firms) and power reliability are complementary, and thus the payoff to labor flexibility is higher where power is more reliable. This makes sense since better power supply would increase the payoff of labor flexibility and the option to expand when business opportunities arise. In addition, our proxy of labor flexibility is complementary with access to finance in India. Again, this makes sense: access to short-term bank loans would boost the return to labor flexibility, for instance, by giving the firm the option to add a work shift by increasing working capital and labor simultaneously.

Our results suggest that the interaction variables have different effects within various regions of the same country. To see this, we compute the marginal effect of an environmental variable R conditional on particular percentiles of a vector of other interacting environmental variables X, or $E\left(\frac{\partial TFP}{\partial R}\middle|X\right) = \beta_R + \beta_{RX}^{'}X$, where β_R measures the direct effect of R, and $\beta_{RX}^{'}$ measures the interaction effects of R and X. We analyze the marginal effects at the median and the 90th percentile of X and present the results in table 8.

[24]Interestingly, Hausman, Rodrik, and Velasco (2005) believe it is difficult if not impractical to identify the indirect effects of reforms.

For India, while the marginal effect of infrastructure quality measured at the median shares of non-permanent workers is negative, as the complementary environmental factor improves to reach the 90th percentile, the marginal effect of infrastructure becomes positive, substantive, and statistically significant. Thus, in India, infrastructure quality matters only in cities which offer more *de facto* labor flexibility (by Indian standards). Similarly, in India, labor flexibility as measured by city share of non-permanent workers has much higher marginal impact on TFP in cities with top 90th percentile power reliability than in cities with the median level power reliability. The city share of large firms does not have much marginal impact on TFP at the median access to finance, but has positive and significant marginal effect at the 90th percentile for the conditioning environmental factor. And access to finance matters much more at the 90th percentile than at the median of the share of large firms. These findings on India echo the finding of policy complementarity found in Aghion et al (2008), though the complementarity detail there differs from ours. In their paper, it is complementarity between product market deregulation and labor flexibility. In our paper, it is between labor flexibility and both access to finance and infrastructure. For China, the fact that we do not find significant complementarity of the various elements perhaps suggests that none of these elements constitute key bottlenecks for China's development.

Robustness Checks

We have used a trimmed sample as a way to deal with outliers by winsorizing the productivity measure at the tail 1 percent. We mentioned earlier that our results would remain qualitatively unchanged if we winsorize at the tail 2 percent or the tail 5 percent. In table 9, we report the results of four additional sensitivity checks. First, we report the robust regression results using the original TFP measure (i.e., without winsorizing). This gives lower weights for observations eligible to be considered as outliers.[25] For the majority of observations, the weight is between 0.90 and 1.00. The results are broadly consistent with those in table 7. A downside of using robust regressions is that they do not accommodate the clustering option, which could exaggerate the estimation precision. Second, we use OLS regressions that allow clustering at the city level for estimating the standard errors, but drop those observations whose weights obtained in the robust regression are in the bottom 1 percent and 5 percent. The results, reported in third and fourth columns in table 9, are again broadly consistent with those in table 7. And finally, we estimate the same empirical specification using median regression (also known as the least absolute value regression), which also has the effect of

[25] This is implemented with Stata's "rreg" command.

downplaying the importance of outliers. Again, we obtain similar results. These robustness checks confirm that our empirical findings are not artifacts of the ways with which we deal with outliers.

V. Conclusion

In this paper, we aim to explore the role of the local business environment in explaining the China–India productivity difference. We find that India has worse skills (or IT), infrastructure, and labor flexibility, but has better access to finance and lower regulation uncertainty. China's large firm sizes along with better skills are the major factors behind its productivity advantage. Infrastructure appears to be a key constraint for India: it lags significantly behind China, yet it has important indirect effects for the effectiveness of labor flexibility. Labor flexibility also appears to be a major constraint for India, as witnessed by the predominance of small firms, the importance of firm size in accounting for the India disadvantage in productivity, and the complementarity of the share of non-permanent workers and the city share of large firms with infrastructure or access to finance. Finally, our results show that productivity effects of the local business environment vary across countries. Average employee skills, for instance, have much stronger payoff in China relative to India. And regulation uncertainty has adverse effects only in India.

Our analysis suggests that a useful way for understanding country-specific economic development is to adopt the growth diagnostic approach (Kremer 1993; Hausman et al. 2005; Aghion et al. 2008). This approach, which we have used here, recognizes that countries may have specific bottlenecks. As a result, a prudent empirical researcher would allow the effects of policies and business environments to vary by country and would take into account the effects of policy interactions. Using this approach, we are able to make meaningful comparisons of total factor productivity between Chinese and Indian firms. We are also able to show that micro studies of firm behavior can be effective in shedding light on growth strategies for countries (Lin and Monga 2010).

Our results also have policy implications. They suggest that India could benefit a great deal from reforms that allow firms to grow in size and from investment in infrastructure. Improvement in labor skills and in the use of information technology in the workplace in India could also help close the performance gap with China.

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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	S.D.	10th percentile	median	90th percentile	mean	S.D	10th percentile	median	90th percentile
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	S.D.	10th percentile	median	90th percentile	mean	S.D	10th percentile	median	90th percentile
City average share of non-permanent workers	0.124	0.039	0.087	0.110	0.177	0.452	0.140	0.280	0.429	0.671
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 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
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 share of senior manager's time spent in dealing with government regulators	0.139	0.064	0.125	0.067	0.220	0.199	0.022	0.199	0.169	0.226
Within-city standard deviation of the share of firm-level senior manager's time spent in dealing with government regulators	0.127	0.062	0.112	0.058	0.217	0.168	0.031	0.161	0.133	0.225

Table 4. Effects of business environment on labor productivity (log value added per employee): common coefficients

China dummy	-0.430***	-0.434***	-0.094	-0.155	-0.187***	-0.258***	-0.207***	-0.676***
	(-3.696)	(-4.263)	(-0.988)	(-1.438)	(-2.901)	(-3.418)	(-2.839)	(-4.149)
$\ln(L_{t-1})$	0.155***	0.135***	0.158***	0.174***	0.159***	0.158***	0.162***	0.131***
	(8.925)	(7.428)	(9.662)	(9.649)	(8.859)	(9.192)	(9.826)	(6.076)
Ln(firm age)	-0.121**	-0.125**	-0.135**	-0.155***	-0.117**	-0.146***	-0.137**	-0.135**
	(-2.139)	(-2.343)	(-2.402)	(-2.839)	(-2.222)	(-2.597)	(-2.480)	(-2.566)
Ln(K/L)*garment	0.363***	0.406***	0.396***	0.397***	0.394***	0.414***	0.399***	0.384***
& leather	(9.071)	(9.269)	(9.440)	(10.631)	(9.364)	(9.765)	(9.662)	(8.776)
Ln(K/L)*eletrical	0.348***	0.358***	0.363***	0.330***	0.330***	0.351***	0.361***	0.319***
	(8.785)	(8.727)	(8.644)	(8.156)	(8.896)	(8.396)	(8.584)	(8.018)
Ln(K/L)*electronics	0.408***	0.415***	0.412***	0.401***	0.407***	0.400***	0.414***	0.398***
	(9.195)	(9.244)	(9.491)	(9.034)	(9.083)	(10.122)	(9.340)	(8.582)
Ln(K/L)*auto & parts	0.425***	0.391***	0.396***	0.377***	0.392***	0.400***	0.397***	0.391***
	(8.562)	(8.199)	(7.885)	(7.474)	(8.022)	(7.762)	(8.004)	(7.923)
Ln(K/L)*food	0.460***	0.448***	0.454***	0.455***	0.452***	0.438***	0.454***	0.429***
processing	(7.530)	(7.448)	(7.557)	(7.619)	(7.791)	(6.840)	(7.532)	(6.890)
Ln(K/L)*chemical	0.425***	0.427***	0.419***	0.405***	0.426***	0.389***	0.421***	0.378***
& pharmaceutical	(10.564)	(10.939)	(10.688)	(8.585)	(10.488)	(8.273)	(10.535)	(7.133)
Ln(K/L)*metal & tools	0.228***	0.223***	0.219***	0.213***	0.237***	0.201***	0.221***	0.214***
	(4.621)	(4.975)	(4.806)	(4.655)	(4.875)	(4.375)	(4.715)	(4.576)
City share of non-	0.849***							0.665***
permanent workers	(3.005)							(3.338)
City share of large		0.577***						0.559***
firms		(3.167)						(2.870)
City share of overdraft			0.268					0.024
access			(1.340)					(0.139)
City power supply				-0.456				-0.677
quality				(-0.495)				(-0.780)
City labor skills					1.109**			0.803*
					(2.553)			(1.783)
City managerial time						1.169*		3.193***
cost						(1.923)		(2.682)
Within-city S.D. of							0.811	-2.768**
managerial time cost							(1.430)	(-2.508)
N observations	2,291	2,429	2,404	2,257	2,381	2,231	2,429	1,951
Adjusted R2	0.351	0.362	0.360	0.358	0.362	0.348	0.358	0.354

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. Effects of business environment on TFP: common coefficients

China dummy	-0.179	-0.138	0.217*	0.168	0.085	0.033	0.105	-0.421**
	(-1.133)	(-0.863)	(1.797)	(1.294)	(1.031)	(0.328)	(1.095)	(-2.248)
$\ln(L_{t-1})$	0.451***	0.441***	0.461***	0.482***	0.462***	0.462***	0.468***	0.425***
	(20.339)	(21.188)	(24.319)	(22.368)	(23.658)	(21.910)	(23.739)	(19.194)
Ln(firm age)	-0.147***	-0.151***	-0.162***	-0.174***	-0.139***	-0.166***	-0.158***	-0.148***
	(-2.616)	(-2.886)	(-2.912)	(-3.148)	(-2.729)	(-2.906)	(-2.859)	(-2.839)
City share of non-	0.958**							0.809***
Permanent workers	(2.485)							(3.140)
City share of large		0.559**						0.555**
Firms		(2.143)						(2.193)
City share of overdraft			0.348					0.070
Access			(1.364)					(0.382)
City power supply				-1.208				-1.250*
Quality				(-1.093)				(-1.667)
City labor skills					1.370***			1.173***
					(2.732)			(2.696)
City managerial time						0.983		3.987***
Cost						(1.348)		(3.446)
Within-city S.D. of							0.313	-3.695***
Managerial time cost							(0.462)	(-3.361)
N observations	2,291	2,429	2,404	2,257	2,381	2,231	2,429	1,951
Adjusted R2	0.625	0.618	0.616	0.620	0.620	0.615	0.615	0.636

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

Table 6. Effects of business environment on TFP: country-specific coefficients

China dummy	0.108
	(0.264)
India * ln(L_{t-1})	0.388***
	(11.887)
India * ln(firm age)	0.054
	(1.156)
India * city share of non-permanent workers	2.093*
	(1.949)
India * city share of large firms	0.286
	(1.043)
India * city share of overdraft facility	0.091
	(0.526)
India * city level of power-supply quality	-1.680**
	(-2.090)
India * city labor skills	-0.002
	(-0.003)
India * city average of share of managerial time on regulators	3.811***
	(3.300)
India * within-city S.D. of the share of managerial time on regulators	-3.929***
	(-2.966)
China * ln(L_{t-1})	0.460***
	(15.642)
China * ln(firm age)	-0.420***
	(-7.971)
China * city share of non-permanent workers	0.327**
	(2.068)
China * city share of large firms	1.047***
	(4.232)
China * city share of overdraft facility	0.158
	(0.463)
China * city level of power-supply quality	4.064
	(0.921)
China * city labor skills	1.630***
	(5.426)
China * city average of share of managerial time on regulators	0.133
	(0.088)
China * within-city S.D. of the share of managerial time on regulators	1.139
	(1.394)
Adjusted R2	0.649

Note. * statistically significant at 10 percent level; **, 5 percent; ***, 1 percent.
Standard errors, clustered at the city level, in parentheses.
Intercept not reported. The number of observations is 1951.

Table 7. Business environment and TFP: Country-specific coefficients with interactions

China dummy	0.972**
	(2.193)
China * city share of non-permanent workers	0.324**
	(2.090)
China * city share of large firms	1.060***
	(4.233)
China * city share of overdraft facility	0.173
	(0.503)
China * city level of power-supply quality	3.973
	(0.921)
China * city labor skills	1.581***
	(5.204)
China * city average of share of managerial time on regulators	0.203
	(0.135)
China * within-city S.D. of the share of managerial time on regulators	1.225
	(1.565)
India * city share of non-permanent workers	10.275***
	(7.493)
India * city share of large firms	-2.941***
	(-3.656)
India * city share of overdraft facility	-0.266
	(-1.238)
India * city level of power-supply quality	-13.950***
	(-6.152)
India * city labor skills	-0.018
	(-0.033)
India * city average of share of managerial time on regulators	4.717***
	(5.784)
India * within-city S.D. of the share of managerial time on regulators	-4.275***
	(-4.495)
India * city share of nonpermanent workers * city infrastructure quality	94.879***
	(5.412)
India * city share of large firms * city access to overdraft facility	4.544***
	(3.621)
Country dummy * ln(L_{t-1}) or ln(firm age)	yes
Adjusted R2	0.652

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 all potential interaction terms. We only kept those interaction terms that are statistically significant at 5 percent levels.

Table 8. Marginal Effects of interacting business environment variables

	Effects of "power reliability"	Effects of "non-permanent"	Effects of "large firms"	Effects of "overdraft access"
X = non-Permanent				
At median X	-3.53 (0.67)***			
At 90th percentile of X	2.87 (1.12)**			
X = power reliability				
At median X		1.75 (0.88)*		
At 90th percentile of X		6.58 (0.89)***		
X = overdraft access				
At median X			-0.27 (0.19)	
At 90th percentile of X			0.58 (0.26)**	
X = share of large firms				
At median X				0.64 (0.17)***
At 90th percentile of X				1.71 (0.41)***

Note. * statistically significant at 10 percent level; **, 5 percent; ***, 1 percent.
Non-permanent = city average share of non-permanent workers.
Large firms = City share of firms with more than 50 employees.
Power reliability = the negative of the city share of losses of sales due to power outage.
Overdraft access = city share of firms with access to overdraft facilities.

Table 9. Dealing with Outliers.

	Robust regression	OLS, drop 5% outliers	OLS, drop 1% outliers	Median regression
china dummy	0.636	0.613	0.880*	-0.221
	(1.098)	(1.437)	(1.931)	(-0.320)
India * city share of non-permanent workers	8.939***	9.588***	9.347***	7.248***
	(4.347)	(6.442)	(7.304)	(2.966)
India * city share of large firms	-2.597***	-2.513***	-2.410***	-2.218*
	(-2.732)	(-3.709)	(-3.242)	(-1.952)
India * city share of overdraft facility	-0.211	-0.227	-0.165	-0.097
	(-0.884)	(-1.205)	(-0.914)	(-0.342)
India * city level of power-supply quality	-12.644***	-13.501***	-11.959***	-11.591***
	(-4.017)	(-5.757)	(-5.641)	(-3.092)
India * city labor skills	-0.311	-0.426	0.134	-0.811
	(-0.477)	(-0.871)	(0.249)	(-1.045)
India * city average of share of managerial time on regulators	4.839***	5.141***	4.815***	4.167***
	(5.370)	(5.825)	(5.788)	(3.874)
India * within-city S.D. of the share of managerial time on regulators	-3.964***	-4.205***	-3.881***	-3.683***
	(-4.218)	(-4.811)	(-4.308)	(-3.298)
India * city share of nonpermanent workers * city infrastructure quality	82.967***	89.180***	78.863***	77.454***
	(3.392)	(5.401)	(4.833)	(2.661)
India * city share of large firms * city access to overdraft facility	4.063***	4.015***	3.754***	3.615**
	(2.983)	(4.148)	(3.300)	(2.224)
China * city share of non-permanent workers	0.281	0.291	0.346**	0.342
	(1.048)	(1.471)	(2.083)	(1.067)
China * city share of large firms	1.242***	1.318***	1.082***	1.199***
	(3.760)	(5.757)	(4.152)	(3.032)
China * city share of overdraft facility	0.183	0.110	0.196	0.230
	(0.440)	(0.362)	(0.529)	(0.466)
China * city level of power-supply quality	3.715	2.092	3.414	2.012
	(0.849)	(0.446)	(0.771)	(0.385)
China * city labor skills	1.308**	1.152***	1.407***	0.997
	(2.417)	(3.434)	(4.203)	(1.540)
China * city average of share of managerial time on regulators	0.454	1.229	0.785	1.792
	(0.179)	(0.912)	(0.461)	(0.591)
China * within-city S.D. of the share of managerial time on regulators	1.328	0.602	0.773	1.726
	(0.784)	(0.791)	(0.962)	(0.850)
Country dummies * firm size or firm age	Yes	Yes	Yes	yes
N obs	1,951	1,854	1,931	1,951
Adjusted R2	0.666	0.733	0.676	

Note. * statistically significant at 10 percent level; **, 5 percent; ***, 1 percent.
Standard errors in parentheses. Standard errors for OLS are clustered at the city level,. Intercept and the interaction of country dummies with firm size or firm age are not reported.

Appendix. The correlation matrix of our key business environment variables

	City share of non-permanent workers	City share of large firms	City share of access to overdraft facilities	City share of loss of sales due to power outages	City share of computer-using staff	City average of time costs
City share of large firms	0.801					
	0.000					
	2493					
City share of access to overdraft facilities	-0.433	-0.302				
	0.000	0.000				
	2575	2624				
City share of loss of sales due to power outages	0.606	0.654	-0.427			
	0.000	0.000	0.000			
	2401	2460	2534			
City share of computer-using staff	0.357	0.445	-0.167	0.196		
	0.000	0.000	0.000	0.000		
	2547	2598	2681	2512		
City average of time costs	0.470	0.552	-0.194	0.553	0.090	
	0.000	0.000	0.000	0.000	0.000	
	2379	2428	2506	2408	2483	
City deal uncertainty	0.369	0.455	-0.101	0.345	0.007	0.815
	0.000	0.000	0.000	0.000	0.719	0.000
	2598	2650	2735	2557	2707	2529

Note. For each cell, the first row represents the coefficient of correlation, the second row the p-value of statistical significance, and the third row the number of observations.