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HUMAN CAPITAL, TECHNOLOGY ADOPTION AND FIRM PERFORMANCE: IMPACTS OF CHINA'S HIGHER EDUCATION EXPANSION IN THE LATE 1990S*

Yi Che and Lei Zhang

We exploit a policy-induced exogenous surge in China's college-educated workforce that started in 2003 to identify the impact of human capital on productivity. Using a difference-in-differences estimation strategy, we find that industries using more human-capital intensive technologies experienced a larger gain in total factor productivity after 2003 than they did in prior years. Exploring the pathways from human capital increases to TFP growth, we find that these industries also accelerated new technology adoption, as reflected in the importation of advanced capital goods, R&D expenditure and capital intensity, as well as employment of more highly skilled individuals. The productivity gains were weaker for domestic private firms than for foreign-owned firms.

Human capital plays an indispensable role in productivity improvement and long-term growth. In developing countries, the lack of skilled labour force poses a major barrier to firms' adoption of frontier technologies that are developed in more advanced economies (Nelson and Phelps, 1966; Caselli, 1999; Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006), thereby restraining efficiency in production. Increases in skilled labour force in a developing country facilitate firms' adoption of frontier technology and hence raise productivity.

We investigate this hypothesis taking advantage of a unique natural experiment in China that substantially expanded college access for high-school graduates starting in 1999, generating a subsequent surge in college-educated workers starting in 2003. This higher-education expansion policy was implemented as part of the economic stimulus plan adopted in the aftermath of the 1997 Asian financial crisis. The centrally-planned nature of the Chinese higher education system means that the ensuing dramatic increase in the college-educated workforce was exogenous to China's economic growth trend, thereby providing a unique opportunity to identify the impact of human capital on technology adoption and productivity. We estimate this impact using a unique panel dataset of privately-owned manufacturing firms for 1998–2007. Using a generalised difference-in-differences (DD) model, we compare the outcomes of firms in more human-capital-intensive industries with those of firms in less human-capital-intensive industries before and after the sharp increase in the college-educated labour

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force. The DD model allows us to eliminate macroeconomic shocks with industry and year-fixed effects. We conduct numerous robustness checks to further deal with potential confounding influences.

We find a significantly larger increase in productivity (measured by total factor productivity, TFP) of firms in more human-capital intensive industries in the post-2003 years relative to 1998–2002. Dynamic analysis shows that, prior to 2003, TFP of firms in all industries followed the same trend but between 2002 and 2003 there was a much larger increase in TFP of firms in more human-capital-intensive industries. Relative TFP stays at this higher level for the rest of the sample period. Robustness checks indicate that the results are not driven by China's accession to the World Trade Organization (WTO) at the end of 2001 or other concurrent macroeconomic shocks, agglomeration effects in specific cities, spillover effects from the reform of state-owned firms, or particular subsets of firms.

There are, however, significant differences between the productivity growth trends of domestic private firms and foreign-owned firms. The relative gains in TFP by domestic private firms in more human-capital intensive industries are much smaller than those of foreign firms: While the TFP of foreign firms in more human capital intensive industries grew relatively faster in the entire post-2003 period, the productivity gains of domestic private firms vanished towards the end of the sample period. This pattern suggests the existence of severe constraints faced by domestic private firms in taking advantage of the increased supply of skilled workers. It also suggests that improvements in credit, taxation, and labour market policies could play important roles in overcoming those constraints.

Overall, relative to 1998–2002 firms in more human-capital intensive industries exhibit larger increases post-2003 in imports of advanced capital goods, capital intensity, R&D expenditure and new product sales. As a result, they have become relatively more important in the manufacturing sector, with larger increases in value added, output and capital stock. These increases have been accompanied by changes in the composition of employment: between 1995 and 2004 there was a relatively larger increase in the employment of more educated workers, as well as workers with the job titles of engineer and technician, in more human-capital intensive industries.

This article contributes to the empirical literature on the role of human capital in technology diffusion and economic growth. Benhabib and Spiegel (2005) demonstrate via cross-country regressions that years of schooling are positively correlated with a country's rate of catch-up to leader nations' TFP. Eaton and Kortum (1996), Coe *et al.* (1997), Xu and Wang (1999), Xu (2000), and Caselli and Coleman (2001) document that technology diffusion through imports of capital goods or foreign direct investment tends to increase the level of a country's human capital. These studies however are beset by problems of human-capital endogeneity and mismeasurement (Bils and Klenow, 2000; Hanushek and Kimko, 2000; Krueger and Lindahl, 2001). More recent studies, such as Becker *et al.* (2011), Lewis (2011), Hornung (2014), and Squicciarini and Voigtländer (2015) use a case study or a historical natural experiment to generate exogenous variation in the quantity of human capital and examine its role in facilitating technology adoption in specific industries and countries at particular times. Methodologically, this article is in the same vein as these recent studies, where causal identification is achieved by using an exogenous shock to the stock of human capital induced by a natural experiment. Additionally, our focus on college graduates provides a more suitable measure of human capital in the context of technology adoption. The rich information from multiple firm-level databases also allows us to explore thoroughly the links among human capital, technology adoption, and productivity in a wider range of industries. These are rarely done in a contemporary developing-country setting.

This article is also related to the literature on the impact of schooling expansion in developing countries. Most of these studies focus on the private returns to individuals who receive more education due to the expansion. Duflo (2001) finds that a large-scale primary school construction programme in Indonesia in the 1970s led to increases in years of schooling and earnings for affected cohorts. Li *et al.* (2014) study the same higher education expansion policy as our article and find negative effects on employment of the cohorts of college graduates affected by the policy. This article complements and extends existing studies by investigating the externality of education expansion, i.e. its impacts on firm productivity and technology adoption.

The article is organised as follows. Section 1 briefly describes the evolution of the Chinese higher education sector and, in particular, events surrounding the expansion beginning in 1999. Section 2 presents the theory underlying the empirical analysis and outlines the estimation strategy. Section 3 describes data sources and summary statistics. Sections 4 and 5 present estimation results on firm productivity, technology adoption and employment changes. Section 6 concludes.

1. Background

1.1. *Higher Education in China*

The central government has been critical in shaping the evolution of China's higher education (HE) sector since the founding of the People's Republic of China in 1949. In the early 1950s, the HE institutions were nationalised and reorganised following the Soviet model, resulting in a dozen or so comprehensive universities and a large number of specialised colleges. Under that model, the central government, based on its economic development plan, makes detailed admission plans for each department in each university and is responsible for the placement of all graduates (Pepper, 1984; Min, 2004). All students are admitted through a unified national college entrance examination (CEE). The HE sector grew steadily in the 1950s, with college enrolment rate increasing from 0.02% of population in 1949 to 0.07% in 1957 (online Appendix Figure A1). This steady growth trend was disrupted by two abnormal developments. The first was the higher-education 'Great Leap Forward', concurrent with the economic 'Great Leap Forward' of 1958 to 1961, when the central government initially planned to achieve universal HE access in 15 years, but that initial period was followed by a severe downsizing in the next four years (Wan, 2006). The second major event was the Cultural Revolution of 1966 to 1976, which all but destroyed China's HE system and reduced HE enrolment by 1976 to a level below that of 1957.

The HE sector returned to a steady growth path in 1977. In the 1990s, to improve its efficiency and its role in local economic development, the central government implemented a series of reforms of the HE sector. These included more responsibilities of provincial governments to finance and administer HE institutions, consolidating institutions to take advantage of economies of scale, substantial tuition payments by college students, and curriculum reforms to broaden the education of students to make them more adaptable in the labour market.[1]

1.2. *Higher Education Expansion since* 1999

During the 1997 Asian financial crisis the Chinese government maintained the value of the renminbi, causing a substantial contraction in exports. The resulting economic downturn and increase in unemployment were compounded by the reforms of the state-owned enterprises (SOEs) that generate a large number of laid-off workers. Against this backdrop, the Chinese Politburo adopted the proposal of Mr. Min Tang, then Chief Economist of the Asian Development Bank's Beijing office, who proposed in late 1998 to 'double college admissions' to stimulate domestic demand for educational services and hence investment in construction, services and other related industries and to postpone high school graduates' entry into the labour market.[2] In January 1999 the Ministry of Education (MOE) announced an admission plan of 1.3 million for three and four-year college programmes, a 20% increase over 1998. The following June it revised the admission plan to 1.56 million, an unprecedented increase of 44% over the previous year.[3]

Annual college admission growth averaged 4.7% between 1995 and 1998, a moderate growth rate largely to accommodate the predicted demand for skilled labour due to economic growth, especially demand of the state sector. In sharp contrast, college admissions grew annually by more than 40% in both 1999 and 2000, and by about 20% over the next five years, before tapering off in 2006 (Figure 1, top panel). By comparison, annual GDP growth rate was around 10% from 1995 to 2005. Nationwide college enrolment doubled between 1998 and 2001 and quadrupled by 2005 (Figure 1, bottom panel, statistics in online Appendix Table A1). The gross college enrolment rate among 18–22 year-olds increased from 9.8% in 1998 to 24.2% in 2009.

All but very few college students graduate on time, so increased admissions translate into increased graduates in about four years, as shown in Figure 2. Because the goal of the higher education expansion policy is to stimulate aggregate demand and is not targeted at any particular sector, the surge in college graduates in the labour force is exogenous to the growth trend of any particular industry or firm and allows credible identification of the causal relationship between human capital and firm economic performance.

[1] The number of majors fell from over1,400 in the mid-1980s to around 200 in 2003 (Min, 2004).

[2] In a letter written to the central government leaders in November 1998, Mr. Tang proposed an 'effective way to stimulate Chinese economy–double the college admission'. The letter was published in a major newspaper on 19 February 1999 (http://finance.sina.com.cn/review/20041023/15201102716.shtml). See also Bai (2006) and Wan (2006).

[3] 'Major Events of Educational Development in 1999', Ministry of Education. URL: http://www.moe.gov.cn/publicfiles/business/htmlfiles/moe/moe_163/200408/3460.html. The continued consolidation of HE institutions and reorganisation within universities such as combining small departments and broadening specialties provides the immediate capacity for expansion. Over time many new campuses are constructed. Faculty-student ratio increases from 5 in 1993 to 15 in 2003, following the new MOE standards.

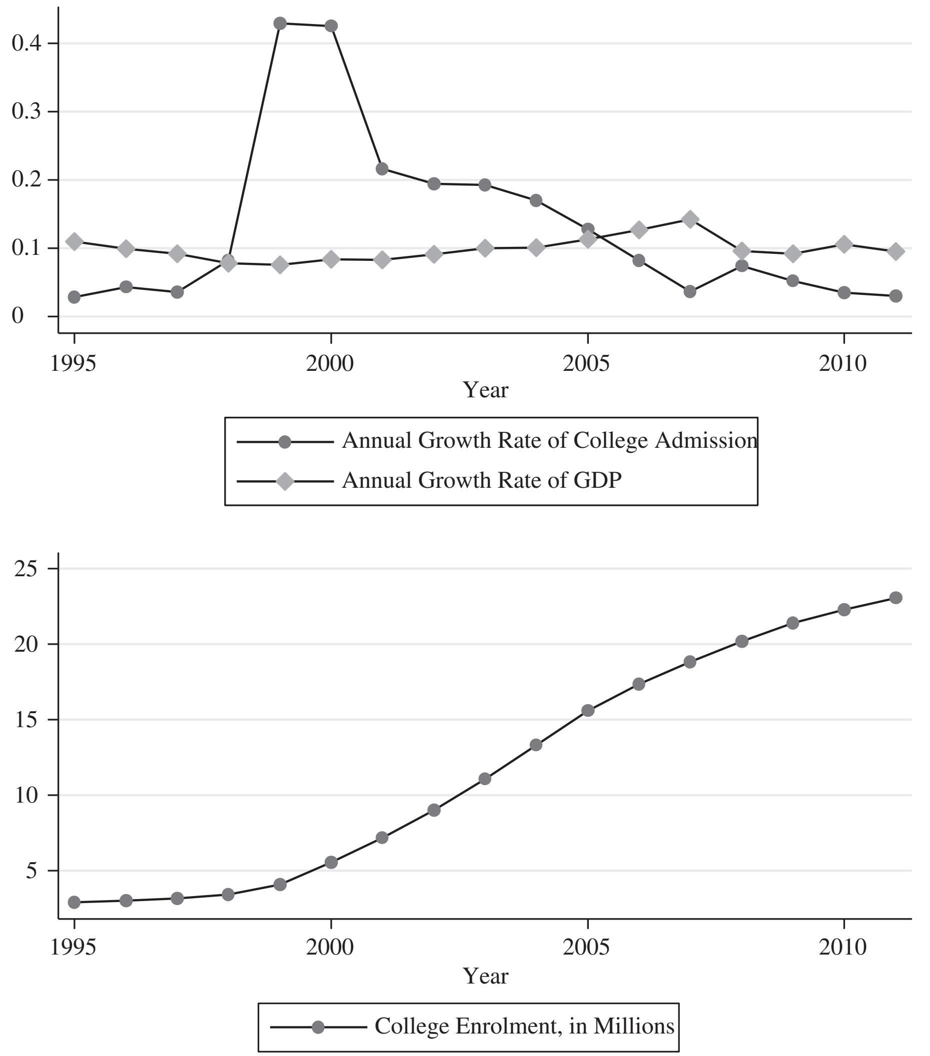

Fig. 1. *Annual Growth Rate of College Admission and Number of College Students Enrolled in Each Year*
Notes. The top panel plots the annual growth rate of college admission, equal to the number of students admitted to three- or four-year regular colleges in current year divided by the number for the previous year minus 1, and the annual growth rate of GDP. The bottom panel depicts the total number of students (in millions) enrolled in regular colleges and universities, including both undergraduate and graduate students. Data are from various issues of China Statistics Yearbook.

2. Analytical Framework

2.1. *A Descriptive Theory of Human Capital, Technology Adoption, and Productivity Growth*

One important reason that firms in less-developed countries have lower productivity than firms in developed countries is a lack of skilled labour. This may lead to the employment of technologies inside the frontier or a mismatch between relatively

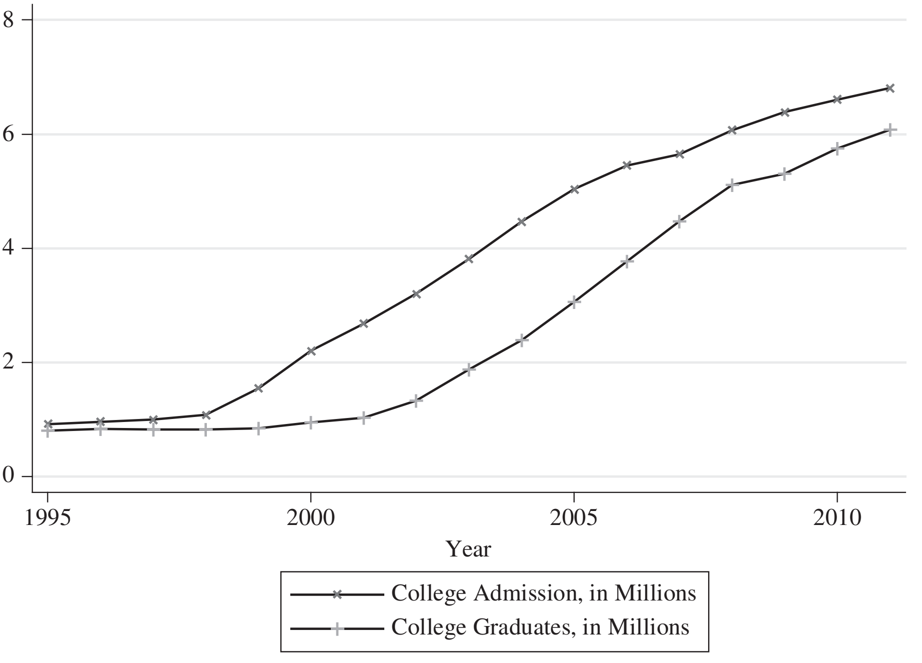

Fig. 2. *College Admission and College Graduates*
Notes. The Figure depicts the total number of students (in millions) admitted to regular three or four-year colleges and universities in each year and the number (in millions) graduated from regular colleges and universities in each year, which include both graduates with an undergraduate degree and those with a graduate degree. Data are from various issues of China Statistics Yearbook.

low-skilled workers and frontier technologies that are primarily invented in developed countries to fit their factor endowments (Acemoglu, 1998; Caselli, 1999; Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006). When the constraint on the stock of skilled workers is substantially relaxed such as through a rapid expansion of formal education, firms may be able to adopt new and more productive technologies, match frontier technologies with more qualified workers, and conduct their own R&D. All of these activities are likely to lead to higher firm productivity and economic growth (Temple and Voth, 1998; Fadinger and Fleiss, 2011; Madsen, 2014).

Meanwhile, the world technology frontier does not progress uniformly across industries. As well documented by Autor *et al.* (1998), Kahn and Lim (1998) and Goldin and Katz (2008), technology progresses since the 1970s are skill-biased, which increases the productivity of workers with higher levels of human capital, such as college graduates, more than those with low levels of human capital, leading also to faster growth in TFP in more human-capital intensive industries.

We conducted informal interviews in several domestic private firms in the suburb of Ningbo in Zhejiang province; their stories bear out the above hypothesis. Two firms manufacturing electric machinery report that the hiring of more college graduates since the early 2000s has benefited their bottom line mainly for three reasons. First, because college graduates are able to read and understand the manuals of delicate tools and computer-automated machines, in particular those in English, they can operate the equipment more efficiently and cause less damage to the equipment. They also translate and post the Chinese labels and instructions for key parts of the equipment, easing the job of other workers. Another advantage emphasised by the managers is that most of the maintenance and repair work can now be done by the new college-educated workers themselves in a timely manner rather than having to wait for the suppliers to provide these services. Second, college graduates' knowledge in technical drawing, circuit design and properties of various materials enables them to quickly translate the intuitive ideas for product improvement of experienced workers and managers into scientific designs and prototypes. The manager of one firm gave the example of an improved electric stacker designed within three months by a group of newly-hired college graduates. Third, the hiring of an increasing number of college graduates allows firms to improve organisation and managerial practices. For example, one firm has adopted the ERP (Enterprise Resource Planning) system. The other two firms make apparel and simple metal products; their increase in the hiring of college graduates is quite modest and these new hires mostly work in marketing and export-related functions. All firms agree that college graduates are quick learners relative to other workers.[4] However, they all express concerns that college graduates, especially those of elite universities, are unwilling to take jobs in manufacturing firms, particularly private firms such as theirs. These are indeed reflected in the heterogeneous estimation results presented in subsection 4.4.

2.2. *Empirical Framework*

Based on the above theoretical analysis and exploiting the exogenous surge in the supply of skilled labour generated by the HE expansion policy, we conduct our empirical analysis in a generalised difference-in-differences (DD) framework, in which we compare changes in performance before and after the HE expansion of firms in more human-capital intensive industries to that of firms in less human-capital intensive industries. The intuition is illustrated in Figure 3, where industries 1, 2, 3 are the high, medium and low human-capital intensity industries, and the height of each bar indicates firm performance in each industry if the frontier technology is employed.[5] Before the higher-education expansion, Industry 3 is at the frontier performance level. Due to the lack of skilled labour, industries 1 and 2 can only reach performance level A, far below the frontier; the gap is particularly large for Industry 1. The HE expansion relaxes the skilled-labour constraint and allows firms in industries 1 and 2 to adopt more advanced technologies. Firm performance in both industries improves, and the increase is larger in Industry 1. In short, the DD method estimates the extra performance increase in Industry 1 relative to that in Industry 2 following the HE expansion.

[4] An alternative view about the role of higher education is that it serves a screening function and selects more capable people. While we are not able to directly test the relative importance of this *versus* the human capital hypothesis, the examples given by firm managers suggest that a college education does impart useful knowledge and skills to students, which allow them to contribute to the firm productivity. Estimation results reported in Table 10 indicate that graduates in the science and engineering fields contribute the most to the relative TFP growth; suggesting that it is the special knowledge graduates learn in these fields rather than their raw talent that enables them to improve the firm productivity.

[5] The ranking of the industry performance by human capital intensity is a simplification assumption.

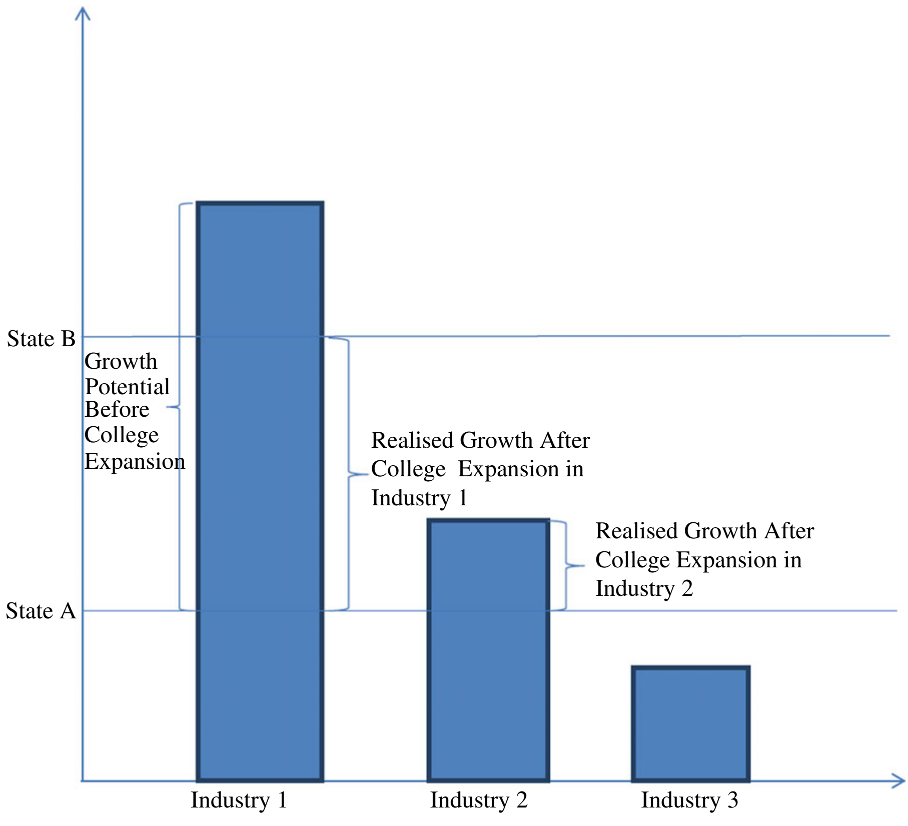

Fig. 3. *Industry Human Capital Intensity and Productivity Growth Post-higher Education Expansion*
Notes. Industries 1, 2 and 3 are the high, medium and low human capital-intensity industries respectively. Height of each column is the firm performance in each industry if the frontier technology is employed. State A is the period before the higher education expansion and it also indicates the highest level of firm performance in Industry 1 and Industry 2. State B is the period after the higher education expansion and it also indicates the highest level of firm performance in Industry 1. Colour Figure can be viewed at wileyonlinelibrary.com.

We implement the DD analysis in the following regression equation:

$$y_{ijt} = \alpha_i + \gamma_t + \beta \times \left(IndustryHC_j \times post_t\right) + \varphi \times X_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where y_{ijt} is a performance measure for firm i in industry j in year t. $IndustryHC_j$ is the human capital (HC) intensity of industry j, measured by the percentage of workers with a four-year college education or more in industry j in the US in 1980. The assumption is that, given the relative flexibility of the US labour market and the fact that the bulk of new technologies in the 1970s were created in a handful of the world's richest countries, with the US leading the way, the industry HC intensity in the US reflects the underlying frontier technology of industries in general. In contrast, a measure based on Chinese industries is likely to be contaminated by policy influences and distortions in resource allocation. This strategy is similar to Hsieh and Klenow (2009), who use the US labour share as a benchmark for Chinese and Indian industries. The variable $post_t$ is an indicator equal to one for 2003 and later years and 0 for years before 2003, since 2003 is the first year when students admitted to a four-year college programme in 1999 graduate and enter the labour market. The coefficient of interest is the estimate on the interaction between HC intensity and the post-2003 dummy, β; it measures the extra increase in y after 2003 relative to prior years for an industry with one percentage point more of college-educated workers. We expect β to be positive if Chinese firms in more HC-intensive industries catch up more rapidly when more skilled workers become available.

The vector α_i is a full set of firm fixed effects to control for firm-specific time-invariant factors such as managerial ability and connections that may affect a firm's performance. Thus, identification of β is based on firms that are in the sample at least once both before and after 2003. This strategy also addresses potential biases in estimation due to firm entry and exit. The vector γ_t is a full set of year fixed effects to control for nationwide economic shocks or policy changes that affect all firms similarly such as monetary policy. Other changes in the economy such as economic openness, financial deepening, and institutional improvement may affect different industries differentially. To address this concern, we control for interactive terms between various industry characteristics and year indicators in X_{ijt}.

One of the most important events during the period under study that may have had potentially large effects on the Chinese economy in general and on specific industries in particular is China's accession to the WTO in late 2001. While the fixed effects and controls in X_{ijt} alleviate potential confounding effects, we conduct numerous robustness checks to further address the potential effects of the WTO accession. These are detailed in subsection 4.2.

We estimate a more flexible version of (1) as follows:

$$y_{ijt} = \alpha_i + \gamma_t + \sum\nolimits_{t=1999}^{2007} \beta_t \times IndustryHC_j \times yr_t + \varphi \times X_{ijt} + \varepsilon_{ijt}, \tag{2}$$

which allows us to inspect the differences in firm performance across industries for each year surrounding the time of the sharp increase in college-educated labour force, relative to 1998. In particular, the pre-2003 trend indicates whether performance of firms in different industries followed the same trend before the surge in college-educated labour force. The absence of a pre-existing trend indicates that the relative changes post-2003 are likely due to the HE expansion.

We first conduct our empirical analysis on firm productivity measured by TFP. We then investigate mechanisms that may lead to TFP improvement such as the adoption of new technologies through the importation of more high-tech capital goods and firms' own R&D activities (Keller, 2010). We also explore changes in the education and skill compositions of firm employees.

3. Data

We combine several data sources for manufacturing firms. First is the 1998–2007 Annual Survey of Industrial Firms (ASIF) maintained by the National Bureau of Statistics of China. The dataset includes all state-owned enterprises (SOEs) and non-SOEs with annual sales over 5 million yuan ('above scale'), about 600,000 US dollars during the sample period, in the mining, manufacturing, and utility sectors. The data contain information about basic firm characteristics and financial variables from firms' balance sheets, income statements and cash-flow statements. We create a panel by matching a firm's Chinese name and numerical ID over the sample period and uniquely match about 85% of firms from the annual surveys.[6] We restrict our sample to domestic private firms and foreign-owned firms. The SOEs are excluded because instead of maximising profits they may take on many social responsibilities and they may also enjoy preferential treatment by the government (Bai *et al.*, 2000), which may bias our estimates.[7] We delete observations with zero or negative values of output, asset stock, sales, or employment.

Table 1 provides summary statistics of the panel for each year of the sample period. The number of private firms in the sample increases from 97,393 in 1998 to 292,800 in 2007 (column 1), as the 5 million yuan criterion for inclusion becomes easier to meet with the rapid expansion of the Chinese economy, in particular that of the private sector. Most of the 'new' firms are not newly created firms but existing ones that grow and become eligible for inclusion in the sample. Firms exit the panel when they shrink, go bankrupt, or are acquired by other firms.[8] The sharp increase in the number of firms in 2004 reflects the fact that the more comprehensive firm census in 2004 identifies a large number of firms that were left out of the annual survey due to imperfect business registry. Columns (2) and (3) report average firm value added and output; at about 10% per year, the growth trend is consistent with China's aggregate growth during this period. Meanwhile, average firm employment decreases (column

Table 1
Summary Statistics of Firm Characteristics

	(1)	(2)	(3)	(4)	(5)
Year	Number of firms	Value added	Output	Employment	Capital
1998	97,393	8,043.1	33,677.9	248.6	14,178.6
1999	98,631	8,681.9	34,963.0	245.0	14,760.0
2000	105,130	9,050.9	36,381.5	237.6	14,688.7
2001	118,676	9,730.1	38,698.7	224.3	14,650.9
2002	133,100	10,639.3	41,722.5	220.3	14,811.8
2003	153,303	11,554.0	45,284.0	217.6	15,217.8
2004	225,575	10,736.4	43,030.9	186.1	13,761.7
2005	228,181	13,561.3	52,919.3	196.1	16,244.0
2006	256,589	16,060.1	62,031.4	191.4	17,298.3
2007	292,800	18,661.0	71,453.8	184.3	17,703.5

Notes. Authors' calculation from the Annual Survey of Industrial Firm (ASIF). Sample includes non-SOE firms only. Sample also excludes firms in the top and bottom 1% of distribution of the TFP estimate. The first column reports number of observations in each year; columns (2)–(5) report averages of firm value added, output, employment, and capital stock. Value added, output and capital are measured in thousand of constant 2007 yuan.

[6] Since a firm's numerical ID may change for various reasons such as a change in ownership, we first use firms' Chinese names to link them across years and then track those firms that cannot be linked in the first step using numerical IDs. Overall, 73.7% of all matches are made by firms' Chinese names and 10.5% using firms' numerical IDs. Additionally, a new industry classification system (GB/T 4754-2002) was adopted in 2003 to replace the old system (GB/T 4754-1994). We convert the industry codes in the 1998–2002 surveys to the new classification system.

[7] A firm is excluded if it is state-owned in any year during the sample period, including SOEs that are later privatised. SOEs are defined based on the reported ownership code in the ASIF data; they generally have at least 95% of state shares. We examine SOEs in our later heterogeneity analysis.

[8] Differences in the number of firms in each year from Brandt *et al.* (2012) are largely due to our exclusion of the SOEs, which account for 33.1% of all firms in 1998 and only 3.4% in 2007.

(4)) and average capital stock increases slightly (column 5), consistent with the entry of many small firms over time.

Our primary measure of firm performance is the TFP estimated from firm input and output variables using the approach proposed by Levinsohn and Petrin, 2003. The advantage of the LP method relative to OLS in estimating TFP is that it smoothly controls for unobserved productivity shocks by using intermediate inputs as proxies.[9] We deflate output, intermediate inputs and capital to their values in terms of the 2007 price level using pertinent deflators obtained from Brandt *et al.* (2012). To ensure that our results are robust to outliers, we drop the top and bottom 1% of estimated TFP in each year. The annual growth rate of our estimated TFP is 9.3%, consistent with that of Brandt *et al.* (2012).

To evaluate the adoption of new technologies when the human capital constraint is relaxed, we use information on imports of capital goods obtained from the 2000–6 China Customs Database, which contains monthly information on the value, quantity, price and source country of import and export transactions at the Harmonised System (HS) 8-digit product level. We merge the Customs data with the ASIF panel using firms' Chinese names. About 43.4% of importing firms are matched to firms in the ASIF panel.[10] We define high-tech capital goods by a number of Chinese key words.[11] The technologies we identify tend to raise the automation level of manufacturing on the factory floor. The installation, operation and maintenance of equipment embodying those technologies require more-educated workers with greater technical, problem-solving and adaptation skills than do more traditional technologies.

We measure firms' imports of capital goods in a given year by their total value, average price and variety. Summary statistics are reported in panel (*a*) of Table 2, where import value and average price are measured in terms of the year 2000 price level. The sample size is much smaller due to the imperfect match between the Customs data and the ASIF data. Over time, the value and average price of imported capital goods generally follow an upward trend but the number of different imported capital goods declines slightly. The top five source countries and regions are Japan, the US, Taiwan, Germany and Russia. As is clear from panel (*b*) of Table 2, importing firms tend to be much larger than the average firm in the ASIF data, and their employment also grows over time. Among all importing firms, 53% import high-tech capital goods, and these firms are even larger than the average importing firm.[12]

Industry HC intensity is measured by the percentage of workers with at least a four-year college education in the same industry in the US in 1980, which comes from Ciccone and Papaioannou, 2009.[13] We recode the industries of Chinese firms to match

[9] The detailed estimation procedure can be found in online Appendix B. Our results are robust to using TFP estimates from the OLS, Olley and Pakes (1996) method and the system-GMM method (Blundell and Bond, 1998), as well as alternative measures of firm efficiency such as value added per worker, output per worker, revenue per worker, and profit per worker. Online Appendix Table A4 reports these estimation results.

[10] Following Ahn *et al.* (2011), we exclude trade companies when merging the two datasets because these are purely intermediaries. Overall, about 15% of all firms in the Customs data are trade companies. Studies using matched datasets of ASIF and China Customs Data include Feenstra *et al.* (2014) and Yu (2015).

[11] These key words in Chinese are 'Shebei', 'Qi', 'Yi', 'Zidong', 'Diannao', 'Weiji', 'Jisuanji', 'Xitong', 'Kongzhi', 'Shuzi', 'Jichuang', 'Xinpian', 'Shukong'.

[12] One reason for this larger size is that smaller firms tend to import through trade companies.

[13] Results of regression analysis are robust to using average years of schooling or percentage of workers with at least a high-school education in the US firms in 1980.

Table 2
Summary Statistics

Panel (*a*): firm capital goods import

Year	(1) Number of firms	(2) Value of capital goods	(3) Average price of capital goods	(4) Number of different capital goods
2000	13,781	440,666.7	6,365	4.3
2001	16,122	526,863.2	7,612.3	4.2
2002	18,297	642,985.1	7,840.7	4.1
2003	20,923	547,110.8	8,430.5	4.1
2004	32,264	638,909.1	8,775.2	4.0
2005	32,522	524,151.3	7,032.2	3.6
2006	35,732	573,171.6	8,530.4	3.2

Panel (*b*): importing firm characteristics

Year	(1) Number of firms	(2) Value added	(3) Output	(4) Employment	(5) Capital
2000	13,781	17,108	72,929	370	35,384
2001	16,122	19,494	80,278	375	37,194
2002	18,297	21,680	87,725	384	37,129
2003	20,923	23,482	96,794	405	38,461
2004	32,264	22,287	97,710	370	36,780
2005	31,522	27,274	116,038	399	41,859
2006	35,732	33,206	139,229	414	46,303

Notes. Authors' calculation from the Annual Survey of Industrial Firms (ASIF) and the Customs Database. Sample includes importing firms in the Customs data that can be matched to the ASIF using firms' Chinese names; firms with zero import of capital goods are included but trade companies are excluded. Value and average price of imported capital goods are measured in constant 2000 US dollars; value added, output, and capital are measured in thousand of constant 2007 yuan.

the industry codes used by CP, which is Revision 2 of the United Nations International Standard Industrial Classification (United Nations, 1968). A total of 28 three-digit industries in the manufacturing sector are included. Table 3 reports the percentage of workers with at least a college education for US industries in 1980 and Chinese industries in 1995 and 2004, with the Chinese information calculated from the 1995 and 2004 firm censuses.

Several features stand out. First, the worker education level in Chinese firms is highly correlated with that of their US counterparts, at 0.67 and 0.73 for 1995 and 2004 respectively, suggesting that the Chinese manufacturing firms are fundamentally similar to the US benchmark in their HC usage.[14] Second and more strikingly, the gap in worker education levels between US and Chinese firms in 1995 is large and highly positively correlated with the worker education level in US firms (0.78), suggesting that Chinese firms lag further behind in more HC-intensive industries, so that firms in these industries have more room to catch up to the technology frontier. Indeed, the increase in the worker

[14] Worker education level is slightly higher for the subsample of above-scale firms and the correlations with that for US firms is somewhat stronger in both years.

Table 3

Industry Education Intensity, USA 1980 and China 1995, 2004

Industry name	(1) ISIC code	(2) US (1980)	(3) China (1995)	(4) China (2004)	(5) Gap (US80-China95)	(6) Gap (US80-China04)	(7) Gap (China04-China95)
		Share of employees with college degree or above					
Food products	311	0.097	0.035	0.105	0.062	−0.008	0.07
Beverages	313	0.131	0.041	0.144	0.09	−0.013	0.103
Tobacco	314	0.110	0.075	0.231	0.035	−0.121	0.156
Textiles	321	0.059	0.026	0.052	0.033	0.007	0.026
Wearing apparel, except footwear	322	0.051	0.015	0.048	0.036	0.003	0.033
Leather products	323	0.071	0.020	0.043	0.051	0.028	0.023
Footwear, except rubber or plastic	324	0.037	0.013	0.040	0.024	−0.003	0.027
Wood products, except furniture	331	0.071	0.022	0.054	0.049	0.017	0.032
Furniture, except metal	332	0.071	0.017	0.065	0.054	0.006	0.048
Paper and products	341	0.109	0.028	0.079	0.081	0.03	0.051
Printing and publishing	342	0.200	0.036	0.108	0.164	0.092	0.072
Industrial chemicals	351	0.217	0.071	0.142	0.146	0.075	0.071
Chemicals, other	352	0.270	0.082	0.232	0.188	0.038	0.15
Petroleum refineries	353	0.250	0.167	0.267	0.083	−0.017	0.1
Misc. petroleum and coal products	354	0.141	0.041	0.098	0.1	0.043	0.057
Rubber products	355	0.079	0.044	0.081	0.035	−0.002	0.037
Plastic products	356	0.102	0.030	0.081	0.072	0.021	0.051
Pottery, china, earthenware	361	0.099	0.023	0.056	0.076	0.043	0.033
Glass and glass products	362	0.087	0.044	0.089	0.043	−0.002	0.045
Other non-metallic mineral products	369	0.142	0.021	0.052	0.121	0.09	0.031
Iron and steel	371	0.083	0.087	0.153	−0.004	−0.07	0.066
Non-ferrous metals	372	0.097	0.088	0.145	0.009	−0.048	0.057
Fabricated metal products	381	0.097	0.034	0.088	0.063	0.009	0.054
Machinery, except electrical	382	0.139	0.072	0.138	0.067	0.001	0.066
Machinery, electric	383	0.163	0.092	0.159	0.071	0.004	0.067
Transport equipment	384	0.159	0.095	0.173	0.064	−0.014	0.078
Professional and scientific Equipment	385	0.185	0.110	0.204	0.075	−0.019	0.094
Other manufactured products	390	0.119	0.017	0.058	0.102	0.061	0.041
Mean		0.123	0.052	0.114	0.071	0.009	0.062
Standard deviation		0.059	0.037	0.064	0.044	0.045	0.034
Correlation with US 1980 measure			0.67	0.73	0.78	0.27	0.66

Notes. This Table reports the human capital intensity for each 3-digit ISIC industry. Column (2) reports share of employees with a four-year college degree or above for US industries in 1980, extracted from table 1 of Ciccone and Papaioannou (2009). Columns (3) and (4) report the share of employees with a three-year college degree or above for Chinese industries in 1995 and 2004 respectively, calculated from Chinese firm census of 1995 and 2004. Columns (5) and (6) report the gap in human capital intensity between US industries in 1980 and Chinese industries in 1995 and 2004.

education level of Chinese firms between 1995 and 2004 is also highly correlated with the US worker education level (0.66). By 2004 the worker education gap between the two countries is no longer significantly correlated with the US worker education level (0.27).[15]

[15] The percentage with college education measure in CP is weighted by hours worked and is for individuals with at least 16 years of education. The measure for the Chinese industry is unweighted and based on individuals with at least a three-year college education.

The top panel of Figure 4 depicts the evolution of the TFP of firms in industries that are above and below median HC intensity separately, with the 1998 values normalised to zero. During the entire sample period, TFP grows continuously for firms in all industries. While TFP in industries with above- and below-median HC intensity track each other closely up to 2002, there is a sharp break of trend in 2003, when industries

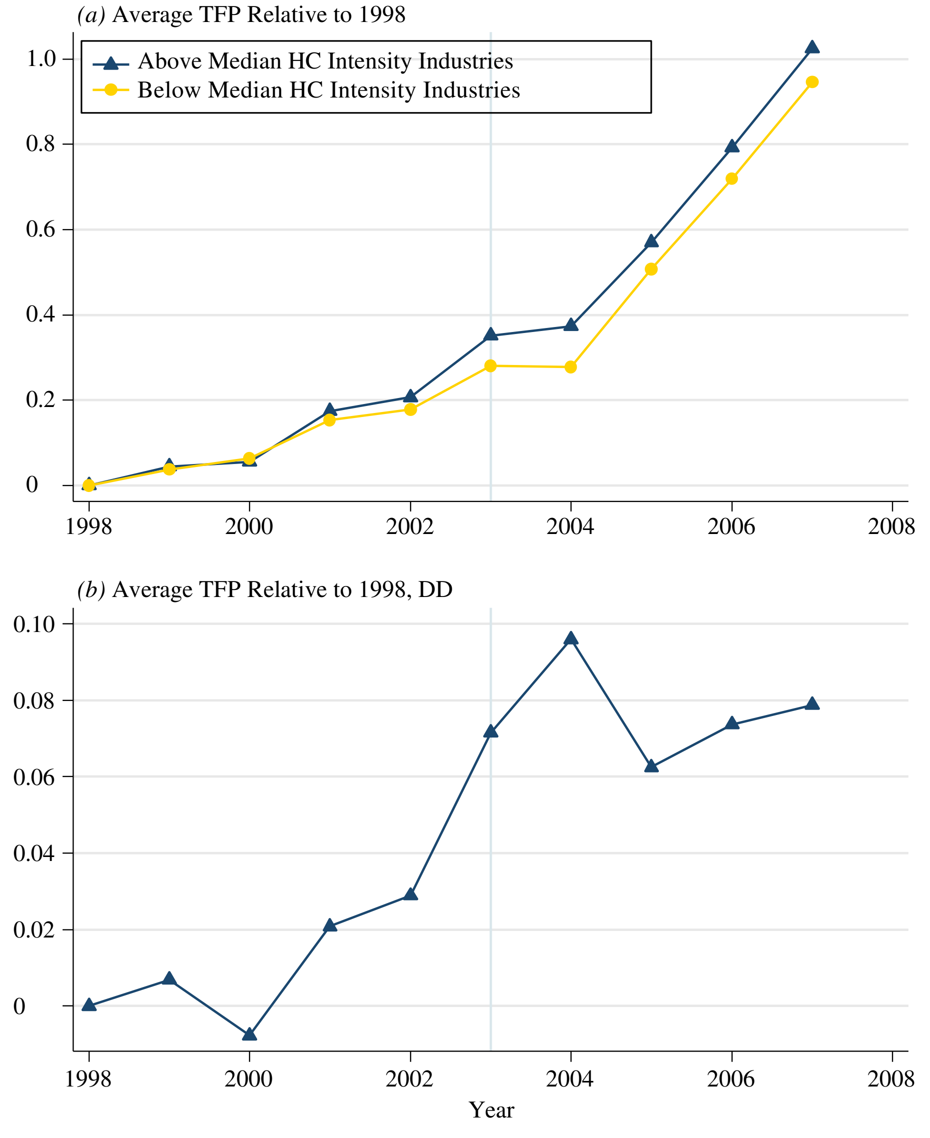

Fig. 4. *Firm Average ln(TFP) by Industry Human Capital Intensity*
Notes. Each data point in the top panels is the average ln(TFP) of all firms in each year-industry cell, with 1998 values normalised to zero. Each data point in the bottom panel is the difference between the two lines in the top panel ($Y_{t,\text{above median}} - Y_{t,\text{below median}}$), with 1998 value normalised to zero. Firm TFP is estimated by the Levinsohn and Petrin (2003) approach. Colour Figure can be viewed at wileyonlinelibrary.com.

with above-median HC intensity exhibit a substantially larger increase in TFP than those with below-median HC intensity. The significantly larger gap in TFP between the two industry groups continues for the rest of the period. The bottom panel more clearly illustrates the changing pattern in relative TFP between the two industry groups for the periods 1998–2002 and 2003–7. The regression analyses to follow are used to parse out confounding factors in order to determine the extent to which this difference in trends can be attributed to the surge in the college-educated labour force.

4. Human Capital and Firm-level Total Factor Productivity

This Section reports estimates of the impact of the surge in the college-educated workforce on the TFP of firms in industries with different human-capital intensities. All standard errors are robust and clustered at firm level to allow for an arbitrary variance-covariance matrix within each firm over time.

4.1. *Baseline Regressions*

Table 4 reports the estimate of the interactive term between HC intensity and the post-2003 dummy of (1). Column (1) controls only for firm and year fixed effects. The estimate on the interaction is 0.273, significant at the 1% level. In the remaining columns we add control variables to address the concern that other concurrent macroeconomic policies may affect the TFP of firms in different industries differentially, and that these industry characteristics may be correlated with HC intensity.

Table 4

Average Effects of Increases in College-educated Labour Force on Firm Total Factor Productivity

	(1)	(2)	(3)	(4)	(5)
	Ln(TFP)	Ln(TFP)	Ln(TFP)	Ln(TFP)	Ln(TFP)
Industry HC intensity × post-2003	0.273***	0.300***	0.285***	0.280***	0.257***
	(0.062)	(0.062)	(0.068)	(0.068)	(0.069)
Capital intensity × year indicators	No	Yes	Yes	Yes	Yes
External Finance × year indicators	No	No	Yes	Yes	Yes
Contract Enforcement × year indicators	No	No	No	Yes	Yes
Province by year FE	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	na
Observations	1,709,375	1,709,375	1,709,378	1,709,378	1,709,378

Notes. Robust standard errors clustered at firm level are in parentheses. ***, **, *Significant at 1%, 5%, 10% level. Sample period is 1998–2007. Dependent variable is the natural logarithm of firm TFP estimated by Levinsohn and Petrin (2003) approach. Industry human capital intensity is measured by percentage of workers with college education or above for each ISIC 3-digit industry in the US in 1980. Capital intensity is measured by share of real capital stock to total value added for each ISIC 3-digit industry in the US in 1980. Both are obtained from Ciccone and Papaioannou (2009). Industry reliance on external finance is defined as capital expenditures minus cash flow from operations divided by capital expenditure for US firms averaged over 1980–9 (Rajan and Zingales, 1998). Industry reliance on contract enforcement is defined as the proportion of intermediate inputs that require relationship-specific investment based on the 1996 US input–output table (Nunn, 2007). Post-2003 equals 1 for 2003–7 and 0 for 1998–2002.

In column (2), we add interactions between industry-level capital intensity and a full set of year indicators, where capital intensity is measured as the ratio between the total real capital stock and total value added of US industries in 1980. If more capital-intensive industries also use human capital more intensively, the estimate in column (1) may pick up the effect of policies that encourage investment. In columns (3) and (4), we further add interactions between the industry degree of reliance on external finance and year indicators and interactions between the industry contract intensity and year indicators.[16] Economic opening in the 1990s is likely to lead to financial deepening and stronger institutions that are conducive to the growth of industries that rely more on the external finance and contract enforcement (Rajan and Zingales, 1998; Nunn, 2007). If these industries are also more HC-intensive, the estimate in column (1) will be biased and partially capture the effects of institutional improvements. Finally, the regional distribution of industries is not random and regions that historically have more industries intensive in human capital may also implement industrial policies that are conducive to the growth of these industries. To alleviate confounding effects due to omitted regional policies, we control for province-year fixed effects in column (5). Estimates on the interaction term in columns (2)–(5) are all positive, highly significant and of similar magnitude to that in column (1). We take the specification in column (5) of Table 4 as our baseline model for the remainder of the article.

The estimate on the interaction between industry HC intensity and the post-2003 dummy in column (5) (0.257) suggests that, on average, TFP growth between 1998–2002 and 2003–7 of firms in the most HC-intensive industry (chemicals, other) is 6 percentage points ($0.257 \times (0.27 - 0.037)$) higher than that of firms in the least HC-intensive industry (footwear). Indeed, for each industry j with HC intensity HC_j, the extra TFP growth relative to the footwear industry is $z_j = 0.257 \times (HC_j - HC_0)$, with $HC_0 = 0.037$ for the footwear industry and we can calculate the extra TFP growth for the entire sector as a weighted sum of the extra TFP growth of each industry $z = \sum_j (s_j \times z_j)$, where the weight s_j is the value-added share of industry j in this sector averaged over 2003–7. The resulting value is $Z = 0.024$. Between 1998–2002 and 2003–7 the overall TFP growth of the above-scale manufacturing firms is 0.41; thus the extra TFP growth due to the HE expansion policy accounts for 5.8% of the overall TFP growth, which is non-trivial given that the employment of college-educated workers increases by just about 6.2% (column (7) of Table 3) in this sector.[17]

Estimates on the interactions between industry capital intensity and year indicators are insignificant between 1999 and 2001 and significantly positive after 2002, and they increase in magnitude from 2002 to 2007. This suggests a possible complementarity

[16] External finance dependence is the industry median of the ratio of capital expenditure minus cash flow to capital expenditure for US firms averaged over 1980–9. Contract intensity is defined as the share of intermediate inputs that require relationship-specific investments, based on the 1996 US input–output table. Measures of capital intensity, external finance dependence, and contract intensity are extracted from Ciccone and Papaioannou (2009), with the original data sources provided in the online Appendix.

[17] By making reasonable assumptions about the contribution to the TFP growth of new college graduates in small firms and SOEs of the manufacturing sector and in the service sector and applying an HC intensity measure for the service sector based on Conti and Sulis (2016), we can similarly calculate the extra TFP growth due to the higher education expansion policy for the entire economy. Online Appendix C provides details of the calculation.

between human and physical capital. Estimates on the interactions between year indicators and the external finance dependence or contract intensity are insignificant in most years and do not show any discernible pattern.

4.2. *Dynamic Regressions*

Table 5 reports estimates on the interactions between HC intensity and year dummies for (2), where we examine the timing of firms' responses to the surge in the supply of skilled labour. Column (1) reports estimates of the baseline model as in column (5) of Table 4. Estimates on the interactions for 1999–2002 are statistically insignificant, suggesting that relative to 1998, firms in more HC-intensive industries did not experience significantly higher TFP growth relative to firms in less HC-intensive industries in the years before the surge of skilled labour. This finding supports our identification assumption that there is no systematic difference in TFP growth across industries before the HE expansion policy-induced surge of college graduates, so it is unlikely that there would have been a post-2003 growth difference were it not for the higher-education expansion policy. In contrast, relative TFP increases sharply in more HC-intensive industries in 2003 and remains at roughly the same level as in 2003 from 2004 to 2007, similar to the pattern depicted in Figure 4.[18]

We note that the estimate on the interaction between HC intensity and the 2002 year indicator, while statistically insignificant, is quite large in magnitude (0.17, compared to 0.007 for 2001). This raises the concern that it may reflect a trend of relative TFP increase of more HC-intensive industries that would have occurred even without the surge in skilled labour that began in 2003. We take several steps to address this concern.

First, the estimate for 2002 may simply be a result of the large increase in graduates from three-year college programmes in 2002, who were admitted in 1999 under the HE expansion programme. As reported in online Appendix Table A1 (columns (4)–(6)), the total number of college graduates increased by 0.3 million (29%) between 2001 and 2002, as a result of a 0.09 million (16%) increase in the number of four-year college graduates and a 0.21 million (46%) increase in the number of three-year college graduates. By comparison, the number of college graduates increased by 0.086 million between 2000 and 2001, of whom 0.072 million were graduates of four-year programmes and 0.014 were graduates of three-year programmes. Thus, the substantial increase in the number of three-year college graduates is plausibly an important contributing factor to the somewhat large estimate in 2002. To complete the picture, we estimate (1) using 2002 as the cutoff year. The resulting estimate on the interaction between HC intensity and the post-2002 indicator (0.273) is significant and slightly larger than that in column (5) of Table 4. This is consistent with the hypothesis

[18] The estimated extra increase in the TFP of more HC-intensive industries is not a spurious relationship due merely to the reduction in the TFP of less HC-intensive industries. As can be seen from the top panel of Figure 4, the TFP of industries of below-median HC intensity also increases during the sample period. Du *et al.* (2014) and Ge and Yang (2014) document the continued influx of rural migrant workers to the industrial sector and their contribution to the productivity of labour-intensive industries.

Table 5

Dynamic Effects of Increases in College-educated labour Force on Firm TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Placebo tests		
	Baseline	Controlling industry trend	Controlling past period Ln (TFP)	Controlling pre-trends (Hornbeck, 2012)	US 1987 SIC 4-digit industry	Taiwan	Japan
Industry HC intensity × 1999	0.099	0.199	0.122	−0.000	−0.273*		0.151
	(0.121)	(0.142)	(0.122)	(0.063)	(0.143)		(0.095)
Industry HC intensity × 2000	−0.100	0.010	−0.079	0.000	−0.379**		0.016
	(0.121)	(0.151)	(0.122)	(0.061)	(0.163)		(0.192)
Industry HC intensity × 2001	0.007	0.131	0.035	−0.000	−0.309*		0.301
	(0.113)	(0.153)	(0.114)	(0.057)	(0.179)		(0.250)
Industry HC intensity × 2002	0.173	0.308*	0.208*	−0.000	−0.214	−0.626	0.402
	(0.119)	(0.162)	(0.121)	(0.054)	(0.223)	(0.805)	(0.281)
Industry HC intensity × 2003	0.354***	0.506***	0.390***	0.543***	−0.199	−1.035	0.389
	(0.108)	(0.159)	(0.111)	(0.051)	(0.236)	(0.893)	(0.304)
Industry HC intensity × 2004	0.359***	0.518***	0.374***	0.600***	0.052	−1.351	0.400
	(0.113)	(0.164)	(0.116)	(0.042)	(0.251)	(0.869)	(0.410)
Industry HC intensity × 2005	0.310***	0.469***	0.310***	0.555***	−0.050		0.289
	(0.112)	(0.163)	(0.115)	(0.042)	(0.289)		(0.476)
Industry HC intensity × 2006	0.175	0.332***	0.197***	0.489***	−0.083		−0.206
	(0.110)	(0.162)	(0.113)	(0.040)	(0.324)		(0.511)
Industry HC intensity × 2007	0.267***	0.423***	0.293***	0.677***	0.527		−0.280
	(0.110)	(0.162)	(0.113)	(0.037)	(0.366)		(0.589)
Capital intensity × year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5

(*Continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Placebo tests		
	Baseline	Controlling industry trend	Controlling past period Ln (TFP)	Controlling pre-trends (Hornbeck, 2012)	US 1987 SIC 4-digit industry	Taiwan	Japan
External finance × year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract enforcement × year indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province by year FE	Yes	Yes	Yes	Yes	N.A.	N.A.	N.A.
Linear industry trend	No	Yes	No	No	No	No	No
1995 industry ln(TFP) × year indicators	No	No	Yes	No	No	No	No
1998–2002 ln(TFP) × year indicators	No	No	No	Yes	No	No	No
Firm/industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE					Yes	Yes	Yes
Observations	1,709,375	1,709,375	1,654,684	1,709,375	4,510	4,944	550

Notes. Robust standard errors clustered at firm level (columns (1)–(4) and (6) and industry level (columns (5) and (7)) are in parentheses. ***, **, *Significant at 1%, 5%, 10% level. Columns (1)–(4) use Chinese firm data; sample period is 1998–2007 and dependent variable is the natural logarithm of firm TFP estimated by Levinsohn and Petrin (2003) approach. Column (5) uses US industry data obtained from the NBER-CES Manufacturing Industry Database; sample period is 1998–2007 and dependent variable is the natural logarithm of TFP in each 1987 SIC 4-digit industry. Column (6) uses Taiwan firm-year level data; sample period is 2000, 2002–4. Column (7) uses industry data obtained from Japan Industrial Productivity (JIP) database; sample period is 1998–2007. Industry human capital intensity is measured by percentage of workers with college education or above for each ISIC 3-digit industry in the US in 1980. Measures of capital intensity, industry reliance on external finance and industry reliance on contract enforcement are the same as in Table 4.

that the large increase in the number of three-year college graduates in 2002 contributed to the relative increase in the TFP of more HC-intensive industries.[19]

Using the large increase in three-year college graduates in 2002 as evidence may not fully dispel concerns about the pre-trend in TFP if the depth and breadth of a three-year college education limit graduates' contribution to firms' performance. To address the concern that other confounding factors may be at work further, we add to the baseline model interactions between industry dummies and the year variable to allow the TFP of each industry to have a different but smooth trend over time. Estimates on the interactions between industry HC intensity and year dummies (reported in column (2) of Table 5) thus capture the additional increase in the TFP of more HC-intensive industries in excess of this smooth trend. Those estimates are all slightly larger than the ones reported in column (1) but the pattern is similar: the estimate is small and insignificant for 1999–2001, increases moderately in 2002, jumps drastically in 2003 and remains at roughly the same level for 2004–7. In column (3) of Table 5, we control directly for the pre-trend in TFP by adding to the baseline model interactions between the past level of TFP and year dummies. One concern this approach helps address is that the 1997 Asian financial crisis may have depressed the TFP of more HC-intensive industries to a larger extent than that of the less HC-intensive industries (so the parallel trend in 1998–2001 reflects this abnormal change), and the TFP only started to revert to the pre-crisis trend in 2003. Controlling for interactions between the TFP of early years and year dummies helps remove the impact of the early-year TFP trend on the TFP of the post-expansion years. Due to data limitation, we can only control for the TFP of 1995.[20] Estimates reported in column (3) are almost identical to those in column (1), suggesting that differences in the TFP between industries before 1997 are not driving our results. The coefficient estimate on the interaction between industry HC intensity and the post-2003 indicator of (1) corresponding to the models of columns (2) and (3) is 0.294 (SE = 0.077) and 0.258 (SE = 0.070) respectively, again similar to our baseline estimate in column (5) of Table 4. Finally, in column (4) of Table 5, we follow Hornbeck (2012) and 'suppress' mechanically the pre-trends by controlling for a full set of interactions between the pre-treatment (1998–2002) values of the dependent variable and year indicators. As expected, estimates on the interactions between industry HC intensity and year dummies before 2003 are all zero but those for 2003 onwards remain large and significant.

Overall, the estimates reported in columns (2)–(4) indicate that our baseline estimates are robust to controls for the pre-trend in TFP in different industries, so that estimates for the post-2003 period are likely to capture the impact of the surge in the

[19] It is also worth noting that prior to 2003 the number of graduates from four-year programmes increases steadily but modestly, by 0.036, 0.055, 0.072, 0.088 million annually between 1999 and 2002; it increases by about 0.27 million annually in each year from 2003 to 2007, a direct outcome of the HE expansion starting in 1999. For three-year programmes, the annual increase prior to 2002 is small but jumps in 2002 and continues to grow through 2007.

[20] The past level of TFP is calculated at the 4-digit industry level from the 1995 firm census, the only year data are available prior to 1998. However, since the 1995 census uses a different firm identification system from later years, we are unable to calculate the past TFP for each firm.

supply of skilled workers on firms' productivity. The estimate for 2002 suggests that graduates of three-year college programmes also contribute to firm productivity.

In columns (5)–(7) of Table 5, we report estimates of (2) using data from various countries; these placebo tests address the concern that our baseline results may just reflect a global trend in the relative TFP growth of different industries. Column (5) reports results for the US, where relative to 1998, estimates are negative and significant for 1999–2001 but insignificant and mostly negative for all later years. Columns (6)–(7) report results for two regions in Asia: Taiwan and Japan, which are likely to have experienced regional economic shocks similar to those affecting China.[21] Estimates for Taiwan (column (6)) are relative to 2000; they are negative, decreasing but insignificant. Estimates for Japan (column (7)) are relative to 1998, and they are generally positive but insignificant.[22] To summarise, none of the three countries exhibits a relative TFP growth trend similar to the Chinese industries. In particular, we do not observe any jump in the TFP of more HC-intensive industries in those countries in 2003. This provides strong evidence that our baseline results are not due to a global trend in the relative TFP growth of different industries.

4.3. *Robustness*: *China's WTO Accession and Other Macroeconomic Shocks*

China's prolonged negotiation with member countries during the 1990s to gain accession to the WTO and its final accession in November 2001 are accompanied by increasing economic openness and institutional improvements (Branstetter and Lardy, 2008), which may not benefit all industries uniformly. This may bias our estimate of the impact of human capital on productivity upward if the industries benefiting disproportionately from the WTO accession are also more HC-intensive and the impact of the WTO accession on productivity occurs with a lag. While the fixed effects and controls of interactions between industry characteristics and year indicators in the baseline model alleviate these confounding effects, we conduct further analysis to address this concern.

First, Chinese firms may gain better access to overseas markets due to lower import tariffs at the destination countries or the elimination of other trade barriers, so that firms in industries that export intensively will benefit more from the WTO accession. To ensure that our results are not driven by exporting industries, we estimate the baseline model excluding the computer and footwear industries, which were the top two exporting industries in China during the sample period. These estimates are reported in columns (1) and (2) of Table 6. In both columns, the estimate on the interaction between industry HC intensity and the post-2003 indicator is positive, significant and similar in magnitude to that in column (5) of Table 4. Column (3)

[21] One advantage of using Taiwan for comparison is that it gained accession to the WTO in 2002, about the same time as mainland China, so the results also help address the concern of China's WTO accession and its impacts on firm performance, which we discuss in detail in subsection 4.2. The drawback however is that the industry coverage of the data we use is quite limited.

[22] TFP data for the US 4-digit industries for 1998–2007 are extracted from the NBER-CES Manufacturing Industry Database. Firm level panel data for Taiwan for the years 2000, 2002, 2003 and 2004 are from Aw *et al.* (2011); the data only cover four industries: consumer electronics, telecommunications equipment, computers and storage equipment, and electronics parts and components. Industry level panel data for Japan spanning 1998–2007 are obtained from the Japan Industrial Productivity Database.

Table 6

Robustness: China's WTO Accession

	(1)	(2)	(3)	(4)	(5)
	Excluding computer industry	Excluding footwear industry	Interaction of export industry dummy with post-2003	Control for firm level tariffs	Control for 2-digit industry level tariffs
Industry HC intensity × post-2003	0.257*** (0.069)	0.264*** (0.069)	0.257*** (0.069)	0.974*** (0.246)	0.262*** (0.069)
Export industries × post-2003			0.223 (0.158)		
Input tariff (firm)				−0.034 (0.034)	
Output tariff (firm)				−0.037 (0.033)	
Input tariff (industry)					0.019 (0.021)
Output tariff (industry)					0.052 (0.040)
Baseline controls	Yes	Yes	Yes	Yes	Yes
Observations	1,708,329	1,682,826	1,709,375	88,701	1,709,375

Notes. Robust standard errors clustered at firm level are in parentheses. ***, **, *significant at 1%, 5%, 10% level. Sample period is 1998–2007. Dependent variable is the natural logarithm of firm TFP estimated by Levinsohn and Petrin (2003) approach. Computer and footwear industries are the top two exporting industries during the sample period; the 'export industry' dummy takes value of 1 for these two industries and 0 otherwise. Each column includes all controls in column (5) of Table 4. Other notes are the same as in Table 4.

includes an interaction between the indicator for the two exporting industries and the post-2003 dummy. The estimate of interest hardly changes.

Second, the WTO accession required China to substantially reduce its import tariffs. The largest and most widespread reduction occurred between 1992 and 1997, with a much smaller one in 2002 and lesser changes in other years. The tariffs on both inputs and final goods follow similar declining trends (Brandt *et al.*, 2012, 2017). Reductions of tariffs on final goods increased the competition faced by Chinese firms in the domestic market, while reductions of input tariffs improved Chinese firms' access to higher-quality and more diverse inputs. Both of these effects may have increased firm productivity (Amiti and Konings, 2007). To mitigate the confounding effects due to potential correlation between tariff reductions and human-capital intensity we include time-varying tariffs on inputs and on final goods as additional controls. In column (4) of Table 6 we control for firm-level tariffs, as in Yu (2015).[23] While insignificant, the

[23] Yu (2015) and Fan *et al.* (2015) argue that, relative to industry level tariffs, firm level tariffs have less measurement error. Firm level output tariff is constructed as $FOT_{it} = \sum w_{ih} \ln \tau_{ht}$, where w_{ih} is the share of exports of product h of firm i in year 2000 obtained from the matched data set of ASIF and China Customs Database; τ_{ht} is the applicable import tariff on product h in year t, downloaded from the WTO website. We use time-invariant weights to avoid potential reverse causality problem from firm productivity to tariffs (Topalova and Khandelwal, 2011). The input tariff is constructed as $FIT_{it} = \sum w'_{ih} \ln \tau_{ht}$, where w'_{ih} is the share of imports of product h in total imports of firm i in 2000. Since imports for processing trade are not subject to import tariffs, we only consider imports in the non-processing categories.

negative estimates on both tariff measures are consistent with the above argument and with Yu (2015). More importantly, the estimate on the interaction between industry HC intensity and the post-2003 indicator remains positive and significant.[24] In column (5), we control instead for average input and final-goods tariffs of 2-digit industries.[25] The estimate on the interaction between industry HC intensity and the post-2003 indicator is significant and almost identical to that in column (5) of Table 4, while estimates on both tariff variables are insignificant.[26]

The WTO accession may have affected industries of different HC intensities differentially via channels other than exports or imports. In addition, other macroeconomic shocks such as industrial policies or credit policies may have affected industries differentially. We address these concerns by taking advantage of the variation in the increase of college graduates across provinces, given that the vast majority of college graduates stay and work in the province of college (Peking University, 2011). If the estimate on the interaction $IndustryHC_j \times post_t$ were due to the differential impacts of economy-wide common shocks on different industries, it would not vary for provinces with different magnitudes of the skilled-labour supply shock, whereas a larger estimate for provinces experiencing a larger supply shock would suggest that the relative TFP improvement is more likely a result of the surge in the supply of skilled labour.

The validity of this strategy hinges on the assumption that the magnitude of the HE expansion is not a response to the expected provincial economic growth and hence the growth in the demand for skilled labour; otherwise, using regional variation may lead to an overestimation of the skilled labour's effect on relative TFP growth. Online Appendix Figure A2 plots the annual growth rates of GDP and college admissions for provinces representing the coastal, central, and western regions of China. In each province, the annual admission growth rate is uncorrelated with the annual GDP growth rate, replicating the national pattern depicted in the top panel of Figure 1. Since we are interested in the impact of the surge of college graduates on the local labour market, we further define the provincial supply shock of college graduates as the difference between the number of new college graduates in 2003 and 2001 relative to the size of the labour force in 2001, focusing on the initial years of the HE expansion. The correlations across provinces between this supply-shock measure and the 1998–9 growth in provincial GDP, TFP of all firms in a province, and TFP of firms in industries with above-median HC intensity are 0.29, 0.14 and 0.21 respectively, none of which is statistically significant. Online Appendix Table A2 provides additional evidence that alternative measures of the

[24] Note that the magnitude of this estimated coefficient is not comparable to that in column (5) of Table 4 due to the much smaller sample size.

[25] Following Amiti and Konings (2007), we obtain industry output tariffs by taking a simple average of tariffs on HS 6-digit products within each 2-digit CIC industry code. The concordance table between HS code and CIC code is from Upward *et al.* (2013). The industry input tariff is constructed as $IIT_{ft} = \sum \bar{w}_{nf} \bar{\tau}_{nt}$, where $\bar{w}_{nf}$ is the share of input n used in producing output f in year 2002 obtained from the 2002 Chinese input–output table. $\bar{\tau}_{nt}$ is the tariff on input n in year t, which is similarly calculated as industry output tariffs.

[26] One caveat is that the measurement of the influence using tariffs is noisier than the measurement of human capital. When both measures are included, it is possible that the more precise measure would be dominant even if the less precise measurement were the most important factor. We thank an anonymous referee for pointing this out.

Table 7

Robustness: Using Regional Variation in College Graduates to Deal with WTO Accession and Other Macroeconomic Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Shock is defined as the increase in new college graduates between 2001 and 2003 relative to 2001 labour force				Shock is defined as the increase in new college graduates between 2000–1 and 2003–4 relative to the labour force in 2000–1		Province-year share of new college grads in the labour force
	Above median	Below median	Top tercile	Bottom 2 terciles	Above median	Below median	
Industry HC intensity × post-2003	0.308***	0.054	0.356***	0.185**	0.300***	0.012	0.215***
	(0.078)	(0.145)	(0.113)	(0.087)	(0.074)	(0.182)	(0.069)
Industry HC intensity × post-2003 × province-year share of new college grads							0.689***
							(0.265)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,272,469	436,906	627,952	1,081,423	1,419,280	290,095	1,709,375

Notes. Robust standard errors clustered at firm level are in parentheses. ***, **, *Significant at 1%, 5%, 10% level. Sample period is 1998–2007. Dependent variable is the natural logarithm of firm TFP estimated by Levinsohn and Petrin (2003) approach. Industry human capital intensity is measured by percentage of workers with college education or above for each ISIC 3-digit industry in the US in 1980. In columns (1)–(4), college graduate shock is defined as the increase in new college graduates between 2001 and 2003 relative to 2001 labour force; in columns (5)–(6), it is defined as the increase in new college graduates between 2000–1 and 2003–4 relative to the labour force in 2000–1. In column (7), we add a triple interaction term between Industry HC Intensity × Post-2003 and province-year share of new college graduates in the labour force. Each column includes all controls in column (5) of Table 4. Other notes are the same as in Table 4.

college-graduate supply shock and provincial economic and productivity growth are uncorrelated.[27]

Columns (1)–(2) of Table 7 present estimation results of the baseline model (column (5) of Table 4) for provinces with an above or below-median college-graduate supply shock. For provinces with an above-median increase in college graduates between 2001 and 2003, the estimate on the interaction between industry HC intensity and the post-2003 indicator is 0.308, which is significant at the 1% level and significantly larger than the baseline estimate. In contrast, the estimate for provinces with a below-median increase in college graduates is insignificant and close to zero. Columns (3) and (4) report results for provinces in the top tercile and bottom two terciles of the distribution of the graduate shock separately. The results follow the same pattern as those in columns (1) and (2). In columns (5) and (6), where the college-graduate shock is defined as the difference between the average number of new college graduates in 2003–4 and that in 2000–1, normalised by the average size of the labour force in 2000–1, the estimates for provinces with an above or below-median college-graduate shock are almost identical to those in columns (1) and (2). Finally, we make use of the time-series variation in the increase in college graduates across provinces by including an interaction between $IndustryHC_j \times post_t$ and the fraction of new college graduates in the labour force in each province in each year. The estimation results are reported in column (7) of Table 7. The estimate on the interaction between industry HC intensity and the post-2003 indicator is 0.215, which is smaller than the baseline estimate. The estimate on the triple interactive term (0.689) is positive and significant at the 1% level.

To summarise, the results reported in Table 7 indicate that provinces with a larger increase in college graduates exhibit a significantly larger increase in TFP in more HC-intensive industries after 2003. This is in contrast to the predicted pattern if all relative TFP growth were due to lagged effects of the WTO accession or other concurrent macroeconomic shocks.

4.4. *Further Robustness Checks*

4.4.1. *Agglomeration*

Beijing and Shanghai have the largest number of universities and college graduates, as well as the most educated labour force in China. They have continued to attract large numbers of college graduates from all over the country in the wake of the higher education expansion. Thus the degree of agglomeration in Beijing and Shanghai may be much higher than in other regions, potentially leading to much larger increases in productivity of firms in Beijing and Shanghai than in other regions, particularly in more HC-intensive industries (see, for example, Moretti, 2004). Column (1) of Table 8 reports estimation results for (1) from a sample that excludes firms in Beijing and

[27] In online Appendix D, we describe in detail that the distribution of universities across provinces is a result of the relocation of universities from the coastal to the inland areas during 1955–7, whose main purpose is to reduce the adverse impacts of potential wars along the coast. The regional distribution of universities taking shape in 1957 persists to the late 1990s and explains a great deal of the college graduate shock.

Table 8

Further Robustness Checks

Variables	(1) Excluding Beijing and Shanghai	(2) Controlling for Spillover effects of SOE reform	(3) Subsample of entrants	(4) Controlling for industry FEs	(5) Balanced panel of firms	(6) Cluster standard errors at different levels
Industry HC intensity × post-2003	0.237*** (0.071)	0.226*** (0.074)	0.318*** (0.116)	0.283*** (0.054)	0.238** (0.104)	0.257 (0.054)* [0.108]** {0.005}***
Industry SOE share 1998 × post-2003		0.039 (0.026)				
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,597,550	1,654,734	300,346	1,709,378	234,700	1,709,378

Notes. Robust standard errors clustered at firm level are in parentheses. ***, **, *Significant at 1%, 5%, 10% level. Sample period is 1998–2007. Dependent variable is the natural logarithm of firm TFP estimated by Levinsohn and Petrin (2003) approach. Column (1) is for the sample excluding firms in Beijing and Shanghai. In column (3), the entrants are firms whose birth year is at most two years prior to the first appearance in the ASIF sample; column (5) is for firms that are in the ASIF sample for the entire 10 year period of 1998–2007. In column (6) the standard error in parentheses is clustered at industry level, that in brackets clustered at province-industry level, that in braces clustered at province-industry level calculated using the Cameron *et al.* (2011) method. Each column includes all controls in column (5) of Table 4 except for column (4), where industry fixed effects instead of firm fixed effects are controlled for. Other notes are the same as in Table 4.

Shanghai. The estimate of interest becomes slightly smaller but remains highly significant, so it does not appear that our baseline results are driven by TFP progress in Beijing and Shanghai alone. This also suggests that college graduates' contribution to the local economy is likely to depend on the local economic environment.[28]

4.4.2. *The influence of the SOE reforms*

During the sample period China carried out dramatic reforms of the SOEs including privatising smaller firms, merging and corporatising larger ones, and creating new, large state-owned firms. The surviving state-owned and privatised firms show fast TFP growth (Hsieh and Song, 2015). Excluding these firms from our analysis mitigates any concern that industry-specific TFP improvements may be the result of within-firm efficiency gains due to the SOE reforms. However, this does not eliminate the potential spillover effects of the SOE reform on privately owned firms in the same industry. To address this concern we include an interaction between the share of SOEs in each industry in 1998 and the post-2003 indicator. We expect the estimate on this interactive term to be positive–intuitively, if an industry has a larger share of SOEs in 1998, it will experience more reforms and hence larger TFP growth in the ensuing years. Results

[28] Another plausible reason for smaller relative TFP increases in regions other than Beijing and Shanghai is the quality of college graduates. Those two cities have the best universities in China and tend to attract the highest quality graduates.

are reported in column (2) of Table 8. The estimate on the interaction between the industry SOE share and the post-2003 dummy is positive but insignificant. Meanwhile, the estimate on the interaction between industry HC intensity and the post-2003 indicator remains positive and significant at the 1% level, although its magnitude is slightly less than the baseline estimate. The estimates are almost identical when we control for interactions between the industry SOE share in 1998 and a full set of year indicators.

4.4.3. *Role of entrants*

Firm entry plays an important role in China's TFP and economic growth (Brandt *et al.*, 2012). To gauge the extent to which the surge in the college-educated labour force may have benefited entrants in more HC-intensive industries we estimate the baseline model on a sample of entrants only, which, as in Brandt *et al.* (2012), are firms that report a birth year at most two years prior to their first appearance in the sample. As reported in column (3) of Table 8, the estimate on the interaction between HC intensity and the post-2003 indicator, 0.318, is significantly larger than the baseline estimate of 0.257, suggesting that the TFP of entrants in more HC-intensive industries improves to a greater extent when skilled labour is more abundant. More generally, column (4) reports results on the entire sample but controlling for industry instead of firm fixed effects. The estimate is 10% larger than the baseline, suggesting that in addition to greater within-firm TFP improvements for more HC-intensive industries, TFP improves within industries, which may result from firm churning within an industry such as entry of more productive firms and exit of less productive ones. Column (5) reports results from a balanced panel of firms, i.e. firms in sample for the entire 1998–2007 period. The estimate is smaller than the baseline, again suggesting resource reallocation within industries as a source of the observed TFP growth.

4.4.4. *Alternative ways of clustering standard errors*

In column (6) of Table 8, we report standard errors clustered at different levels. First, since we exploit variation in HC intensity across industries, following Bertrand *et al.* (2004), we report standard errors clustered at the industry level in parentheses. The standard error on the interactive term becomes slightly larger, but the coefficient estimate remains significant at the 10% level. Second, local governments in China generally have a strong influence over local economic policies and economic environments (Xu, 2011), so the error term may be serially correlated within each province-industry cell. We report a simple standard error clustered at the province-industry level in square brackets, and a standard error calculated using the two-way clustering method proposed by Cameron *et al.* (2011) in braces. The coefficient estimates are significant at the 5% and 1% level respectively. In sum, the baseline estimate remains robust to alternative methods of calculating standard errors.

4.5. *Heterogeneous Responses of Firms of Different Ownerships*

One important feature of the Chinese economy is that domestic private firms and foreign firms may face different incentives and constraints, which may lead to different responses when the constraint of skilled labour is relaxed. We explore these differences in this subsection. For further comparison, we conduct separate analyses for SOEs.

Panel (*a*) of Table 9 reports the average effect estimated from the baseline model. The extra TFP increase in more HC-intensive industries after 2003 is substantially larger for foreign firms (0.9) than for domestic private firms (0.145); it is also significant both statistically and economically for SOEs (0.79). In panel (*b*), we present dynamic estimates for the three types of firms. For both domestic and foreign firms, estimates on the interactions between HC intensity and indicators for the years before 2003 are mostly small and insignificant but the estimate is again larger for 2002 than for earlier years, suggesting the influence of the increase in three-year college graduates. The estimate for 2003 is significant and much larger for both types of firms,

Table 9

Heterogeneous Responses by Firm Ownership

Variables	(1) Domestic private firms	(2) Foreign firms	(3) SOEs
Panel (*a*)			
Industry HC intensity × post-2003	0.145**	0.900***	0.794***
	(0.072)	(0.187)	(0.209)
Panel (*b*)			
Industry HC intensity × 1999	0.052	0.382	0.657***
	(0.126)	(0.361)	(0.236)
Industry HC intensity × 2000	−0.107	0.179	0.482*
	(0.126)	(0.348)	(0.256)
Industry HC intensity × 2001	0.032	0.281	0.554**
	(0.117)	(0.319)	(0.278)
Industry HC intensity × 2002	0.189	0.577*	1.085***
	(0.124)	(0.338)	(0.306)
Industry HC intensity × 2003	0.313***	0.936***	1.486***
	(0.113)	(0.297)	(0.307)
Industry HC intensity × 2004	0.264**	1.095***	1.868***
	(0.117)	(0.319)	(0.364)
Industry HC intensity × 2005	0.215*	1.104***	1.077***
	(0.118)	(0.307)	(0.359)
Industry HC intensity × 2006	0.026	1.223***	0.763**
	(0.115)	(0.302)	(0.362)
Industry HC intensity × 2007	0.044	1.605***	0.962***
	(0.115)	(0.302)	(0.368)
Observations	1,408,005	301,373	250,810
Panel (*c*)			
Industry HC intensity × post-2003			
Above median college grad shock	0.208**	0.977***	0.704***
	(0.082)	(0.185)	(0.270)
Observations	1,039,018	233,451	161,256
Below median college grad shock	−0.092	0.612	0.924***
	(0.155)	(0.403)	(0.325)
Observations	368,990	67,916	89,556

Notes. Robust standard errors clustered at firm level are in parentheses. ***, **, *Significant at 1%, 5%, 10% level. Sample period is 1998 to 2007. Dependent variable is the natural logarithm of firm TFP estimated by Levinsohn and Petrin (2003) approach. Industry human capital intensity is measured by the percentage of workers with college education or above for each ISIC 3-digit industry in the US in 1980. Models are the same as that in column (5) of Table 4 (panels (*a*) and (*c*)) and column (1) of Table 5 (panel (*b*)). College graduate shock is defined as the increase in college graduates between 2001 and 2003 relative to the 2001 labour force in a province. Each regression includes all controls in column (5) of Table 4. Other notes are the same as in Table 4.

but estimates for the years after 2003 follow quite different patterns. Foreign firms in more HC intensive industries exhibit large and continued improvements in TFP relative to other firms, whereas domestic private firms in more HC-intensive industries display much smaller TFP increases during 2003–5 relative to other firms and there are almost no relative TFP gains from 2006 to 2007.[29] This explains the flat relative TFP growth pattern for all firms reported in Table 5 given the weight of private firms in the entire sample. In contrast, the dynamic estimates indicate that the TFP growth of SOEs in more HC-intensive industries was significantly larger than that of SOEs in other industries before the higher education expansion, but the gap widens even more after the expansion.

The larger responses of foreign-owned firms relative to domestic private firms may raise a concern about sorting; i.e. during that time period skilled labour may have self-selected into more productive foreign firms and shunned the less productive domestic private firms that may have been further from the technology frontier. To address this concern, we estimate separate regressions for provinces with above or below-median college graduate shocks as defined in subsection 4.2. If the previous estimation results are mostly due to sorting, then within each type of firms estimates for provinces experiencing different college graduate shocks would not differ substantially if sorting is similar across provinces. As reported in panel (*c*), for both the domestic private firms and foreign-owned firms the estimate on the interactive term between industry HC intensity and the post-2003 indicator is substantially larger for provinces with larger skilled-labour supply shocks. This is more consistent with the interpretation that the relative TFP improvement after 2003 is attributable to the increase in the supply of skilled labour rather than sorting of skilled labour into more productive firms.

The patterns of relative TFP increase are consistent with the findings of Yue *et al.* (2016) that, of the 2003–13 graduate cohorts, domestic private firms tend to hire less-skilled, three-year college graduates and four-year graduates from lower-tier universities, while SOEs and foreign-owned firms are much more likely to hire four-year graduates and those with post-baccalaureate degrees. The different patterns between domestic and foreign firms may have several explanations related to the complementarity between skilled labour and investment in frontier technologies. First, foreign-owned firms may have better information about the frontier technology and better access to overseas markets for advanced capital goods. Second, foreign firms may face less severe credit constraints than domestic firms (Manova *et al.*, 2015), thereby more able to carry out new investment. Third, during the sample period foreign firms received preferential tax treatment relative to domestic firms, which may give them more incentives to carry out new investment.[30]

[29] The industry HC-intensity measure based on 1980 US data is likely a less precise, albeit more exogenous, measure of the HC intensity of Chinese firms in 2003–7. In online Appendix Table A3, we report estimation results using the education composition of Chinese industries in 1995 to measure industry HC intensity. For firms of all ownership types, both the average effect estimate and the dynamic estimates for the post-2003 period are much larger and more precisely estimated than those reported in Table 9. In particular, for domestic private firms the estimates for all of 2003–7 are significant and increasing slightly over time. Thus, estimates using the 1980 US industry HC intensity likely underestimate the effects of the surge in the supply of skilled labour on relative TFP improvement. We thank an anonymous referee for pointing this out.

[30] We conducted a thorough search of tax policies for the sample period and did not find any industry-specific tax credits targeted at foreign-owned firms.

5. Human Capital and Firms' Technology Adoption

This Section investigates pathways through which a surge in the skilled labour force could spur firms' productivity. Skilled labour may enhance firms' productivity by facilitating the adoption of new technologies and new production organisations. This may be more plausible for firms in more human capital-intensive industries given the rapid progress in skill-biased technologies in recent decades. We focus on two types of firm activities: the importation of high-tech capital goods and firms' own innovation activities. We also explore changes in the education and occupation composition of firms' employees.

Before moving on to investigating firms' adoption of new technologies, we test a direct prediction of our hypothesised mechanism: College graduates in science and engineering (S&E) fields may contribute more to firms' productivity than graduates of other fields. Making use of the variation in the number of graduates of different fields across provinces and over time, we estimate the same model as that of column (7) of Table 7, where we interact $IndustryHC_j \times post_t$ with the province-year share of new graduates of various fields in the labour force. Columns (1)–(3) of Table 10 report estimates separately for the science and engineering fields, economics, management and law (EML) fields, and other (humanities, education, medicine, and agriculture) fields.[31] As expected, with an estimate of 3.07 on the triple interaction and significant at the 1% level (column (1)), more HC-intensive industries in provinces with a larger increase in graduates of the S&E fields exhibited a significantly larger relative increase in TFP after 2003. The estimate for the EML fields is moderate and marginally significant (1.532, SE = 0.838), suggesting a plausible role of graduates of these fields in improving firm organisation and management. In contrast, the estimate for other fields is much smaller and insignificant. In column (4) we add simultaneously triple interactions with the share of the S&E fields and EML fields. The estimate for the S&E fields continues to be large (2.587) and significant but that for the EML fields is close to zero.[32] Overall, the results in Table 10 are consistent with our hypothesis that increases in the supply of college graduates boost firms' productivity mainly through the technology-diffusion channel.[33]

[31] Data on the number of graduates of different fields by province-year are from various issues of the provincial statistics yearbooks. No data are available for eight provinces including several with a large number of industrial firms (Guangdong, Shandong, Zhejiang, Beijing), and data are missing for seven provinces in various years. This substantially reduces the sample size.

[32] Due to multicollinearity, the triple interaction with the graduate share of other fields is omitted from the regression.

[33] College graduates of different majors also tend to work in different industries, and the S&E majors are more likely to work in the manufacturing industry than other majors and hence their larger contribution to the relative TFP growth of manufacturing firms. Based on surveys of nationally representative samples of college graduates in 2009 and 2011 conducted by researchers of Peking University, the top three industries S&E majors enter are manufacturing (24%), telecommunication (16%), and electricity, gas and water (11%); the top three for EML majors are finance (19%), manufacturing (12%), and telecommunication (8.4%); and the top three for other majors are education (22%), manufacturing (10%) and health and social security (8.9%). Survey data are courtesy of Professor Changjun Yue of Peking University.

Table 10

Effects of Increases in College-educated Labour Force of Different Academic Fields on Firm TFP

Variables	(1) Science and engineering	(2) Economics, management, and law	(3) Other fields	(4)
Industry HC intensity × post-2003	0.044	0.075	0.152	0.053
	(0.093)	(0.079)	(0.096)	(0.093)
Industry HC intensity × post-2003 × prov-year share of science and engineering grads in labour force	3.072***			2.587**
	(0.748)			(1.297)
Industry HC intensity × post-2003 × prov-year share of econ, management, law grads in labour force		1.532*		−0.154
		(0.838)		(1.538)
Industry HC intensity × post-2003 × prov-year share of other grads in labour force.			1.341	
			(1.247)	
Baseline controls	Yes	Yes	Yes	Yes
Observations	940,021	916,355	892,889	916,355

Notes. Robust standard errors clustered at firm level are in parentheses. ***, **, *Significant at 1%, 5%, 10% level. Sample period is 1998–2007. Provincial data on number of graduates of each field are from various issues of provincial statistics yearbooks. No data are available for eight provinces including several with a large number of industrial firms (Guangdong, Shandong, Zhejiang, Beijing), and data are missing for seven provinces in various years. Dependent variable is the natural logarithm of firm TFP estimated by Levinsohn and Petrin (2003) approach. Industry human capital intensity is measured by percentage of workers with college education or above for each ISIC 3-digit industry in the US in 1980. 'Other fields' include humanities, education, agriculture, and medicine. Each regression includes all controls in column (5) of Table 4. Other notes are the same as in Table 4.

5.1. *Firms' Imports of High-tech Capital Goods*

The analysis in this subsection is conducted on the merged Customs and ASIF data, which means that we miss the activities of relatively small firms. To set the stage, we first verify that more HC-intensive industries exhibited larger increases in TFP after 2003 relative to previous years for this smaller sample. The estimate of the average effect (panel (*a*) of Table 11, column (1)) is positive, significant but larger in magnitude than the baseline estimate.[34] The dynamic estimates (all relative to 2000) in panel (*b*) follow the same pattern as those in column (1) of Table 5.

Estimates for various measures of firms' imports of high-tech capital goods are reported in columns (2)–(4) of Table 11, with all baseline controls included. We first discuss the average effect estimates (panel (*a*)). In column (2), the dependent variable is the natural logarithm of the total value of imported capital goods.[35] Consistent with our hypothesis, firms in more HC-intensive industries exhibited larger increases in the importation of high-tech capital goods after 2003: The estimate on the interaction term is 2.95 and significant at the 1% level. Column (3) examines, conditional on

[34] Note that the pre-period is 2000–2.

[35] Since the sample includes firms with zero import of high-tech capital goods, the dependent variable in column (2) is the natural logarithm of 1 plus the total import value.

Table 11

Impact of Increases in College-educated Labour Force on Firm's Technology Adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(TFP)	Ln(1 + value of imported high-tech capital goods)	Ln(average price of imported high-tech capital goods)	Number of different high-tech capital goods	Ln(capital stock per worker)	Ln(1 + research investment)	Ln(1 + training investment)	Ln(1 + value of new products)
Panel (*a*)								
Industry HC intensity × post2003	0.872***	2.949***	1.493**	0.238	0.321***	0.853***	0.486***	0.480***
	(0.232)	(0.725)	(0.633)	(0.749)	(0.119)	(0.153)	(0.110)	(0.152)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel (*b*)								
Industry HC intensity × 1999								0.116
								(0.182)
Industry HC intensity × 2000								−0.083
								(0.189)
Industry HC intensity × 2001	0.011	−0.237	1.393	0.640	0.104			−0.078
	(0.343)	(1.073)	(0.997)	(0.906)	(0.147)			(0.197)
Industry HC intensity × 2002	0.112	1.519	1.021	0.372	0.309**	0.214	−0.062	0.145
	(0.381)	(1.091)	(1.010)	(0.945)	(0.149)	(0.132)	(0.101)	(0.197)
Industry HC intensity × 2003	0.786***	2.573***	1.663*	0.476	0.428***			0.378*
	(0.342)	(1.082)	(0.979)	(1.002)	(0.159)			(0.198)
Industry HC intensity × 2004	1.062***	2.756***	1.922**	1.291	0.517***			
	(0.352)	(1.075)	(0.979)	(1.077)	(0.166)			
Industry HC intensity × 2005	0.793**	4.772***	3.053***	0.277	0.440**	0.609***	0.079	0.705***
	(0.343)	(1.095)	(1.016)	(1.078)	(0.172)	(0.171)	(0.087)	(0.230)
Industry HC intensity × 2006	1.059***	4.053***	2.432***	0.027	0.444**	1.058***	0.244***	0.589**
	(0.339)	(1.119)	(1.038)	(1.135)	(0.181)	(0.176)	(0.093)	(0.238)
Industry HC intensity × 2007						1.263***	0.371***	0.419*
						(0.182)	(0.099)	(0.241)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168,641	169,332	89,372	169,332	168,641	1,029,300	1,254,833	1,483,802

Notes. Robust standard errors clustered at firm level are in parentheses. ***, **, *Significant at 1%, 5%, 10% level. Sample for columns (1)–(5) is importing firms in the 2000–6 Customs Data matched to the ASIF database. Column (2) includes only firms with a positive import value of high-tech capital goods. Sample for columns (6)–(8) is from ASIF. Sample period for columns (6) and (7) is 2001, 2002, and 2005–7, for column (8) is 1998–2003 and 2005–7. Industry human capital intensity is measured by percentage of workers with college education or above for each ISIC 3-digit industry in the US in 1980. Each regression includes all controls in column (5) of Table 4. Other notes are the same as in Table 4.

importing, whether firms in more HC-intensive industries were more likely to import higher-quality capital goods after 2003, where quality is measured by the average price of imported capital goods. Again, this is borne out by the positive and significant estimate on the interaction. In column (4), we consider the number of different capital goods (at HS 8-digit level) imported by each firm. The estimation result, positive but insignificant, suggests that firms in more HC-intensive industries likely substituted more-expensive types of capital goods for less-expensive ones. Given the larger increases in investment in high-tech capital goods by more HC-intensive industries, we expect larger increases in capital intensity of these industries. In column (5), the estimate on the interactive term is positive and significant for the regression of firm capital-labour ratio, confirming our hypothesis.

Columns (2)–(5) in panel (*b*) of Table 11 report the results of the baseline dynamic model for each variable. For the total value and average price of imports and capital intensity, the estimate on the interaction term for 2001 is small and insignificant. The estimate for 2002 is larger but generally insignificant, whereas estimates for 2003–7 are positive and significant both statistically and economically. This pattern suggests that firms carried out capital goods investment simultaneously with the arrival of the new college-educated workers. However, since firms could predict this surge in the supply of college-educated workers, it is likely that they made their investment plans in advance. Estimates for the number of different capital goods imported are insignificant.

5.2. *Firms' Innovation Activities*

The large increase in the college-educated labour force may have enabled firms to perform various innovative activities. First, firms may have boosted their own research and development (R&D) activities to facilitate the assimilation of the newly imported high-tech equipment, to improve their production process and organisational practice, to improve existing products and to create new products. Second, since training is more valuable for more educated workers with higher learning ability, firms may have spent more on worker training, which is also necessary to install, operate, maintain and improve on new production equipments. All these activities are likely to be conducive to firm productivity.

Columns (6)–(8) of Table 11 report estimates on the interactive term between industry HC intensity and the post-2003 indicator (panel (*a*)) and those between industry HC intensity and year dummies (panel (*b*)) using our baseline specification. In columns (6)–(7), the dependent variables are the natural logarithm of 1 plus firm spending on R&D and worker training respectively. Due to missing data, the pre-expansion period includes 2001 and 2002 and the post-expansion period 2005–7. In both columns, we find a positive and significant (at 1% level) effect of the HE expansion on firms' innovative activities. Although data for 2003 and 2004 are missing, there appears to be an increasing trend in 2005–7 for both variables. In column (8), the dependent variable is the natural logarithm of 1 plus the value of a firm's new products, which may be regarded as a direct measure of product innovation. In this case, data for 2004 are missing. Estimate on the interactive term is positive and significant at 1% level. In the dynamic model, the estimate becomes significant in 2003 and increases in later years.

To summarise, the findings in Table 11 – that firms' imports of high-tech capital goods and innovation activities increased more in more HC-intensive industries after 2003 – suggest that these activities are plausible channels through which firms in more HC-intensive industries achieved relatively larger increases in TFP after 2003. These results also suggest a strong complementarity between skilled labour and capital inputs. Thus, in circumstances where there are big barriers to investment, skilled labour may be less effective in improving firm productivity.

5.3. *Changes in Firms' Employment Composition and Average Wage*

Our hypothesis that the surge in the supply of the college-educated labour force led to a relative increase in the adoption of new technologies and consequent productivity gains in relatively HC-intensive industries, implies that firms in more HC-intensive industries increased to a larger extent the hiring of better-educated workers and in more-skilled occupations after 2003.

The industry censuses of 1995 and 2004 contain information on the percentage of workers with different levels of education and employed as engineers and technicians for each firm; we use the latter to measure employment in the skilled occupations.[36] However, since the ID coding system for firms changed between the two censuses and firm names are not reported in the 1995 census, we are unable to link the two data sets at the firm level. We thus aggregate the firm-level information to the 4-digit industry level. We restrict the sample to above-scale firms and estimate the following equation:

$$\Delta EmpShare_{kj} = \beta_0 + \beta_1 \times IndustryHC_j + \theta \times \mathbf{X}_j + \omega_{kj}, \quad (3)$$

where $\Delta EmpShare_{kj}$ is the change in the share of employees with a particular characteristic between 1995 and 2004 in 4-digit industry k belonging to 3-digit ISIC industry j; $IndustryHC_j$ is the HC intensity of 3-digit ISIC industry j as in (1); and $\mathbf{X}_j$ is a vector of control variables for 3-digit industry characteristics including physical-capital intensity, reliance on external finance, and reliance on contract enforcement. The variable ω_{kj} is a stochastic error term.

Columns (1)–(4) of Table 12 report the estimation results of (3), with robust standard errors clustered at 3-digit ISIC industry level reported in parentheses. The first three columns consider changes in worker education composition between 1995 and 2004. Over the 10-year period straddling the HE expansion, firms in more HC-intensive industries increased to a significantly larger extent their hiring of college educated workers (column (1)) and, to a lesser extent, workers with a high school education (column (2)). This was accompanied by a significantly larger reduction in the employment of workers with less than high-school education (column (3)), of a magnitude roughly the same as the growth in college educated workers. Finally, the estimation result in column (4) indicates that more HC-intensive industries also experienced a significantly larger growth in the fraction of workers in engineer and technician positions, consistent with more innovative activities estimated in Table 11.

[36] Another type of skilled occupation is managerial positions. This information is included in the 1995 census but not in the 2004 census.

Table 12

Change in Education and Occupation Composition between 1995 and 2004 and Wage Dynamics

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: difference between 1995 and 2004 in industry percentage of employees					
	With college degree or above	With high school education	With junior high school edu or below	Who are technician or engineers	Ln(average wage)	
Industry HC intensity	0.491*** (0.073)	0.227*** (0.063)	−0.460*** (0.098)	0.331*** (0.054)		
Industry HC intensity × Post2003					0.022 (0.026)	
Industry HC intensity × 1999						0.013 (0.040)
Industry HC intensity × 2000						0.063 (0.041)
Industry HC intensity × 2001						0.134*** (0.041)
Industry HC intensity × 2002						0.211*** (0.040)
Industry HC intensity × 2003						0.201*** (0.040)
Industry HC intensity × 2004						0.140*** (0.038)
Industry HC intensity × 2005						0.081** (0.039)
Industry HC intensity × 2006						0.119*** (0.039)
Industry HC intensity × 2007						0.043 (0.040)
Observations	426	426	426	426	1,709,378	1,709,378

Notes. Robust standard errors clustered at industry level are in parentheses. ***, **, *Significant at 1%, 5%, 10% level. Data for columns (1)–(4) are 4-digit industry level data aggregated from the 1995 and 2004 firm censuses. Data for columns (5)–(6) are from the ASIF database, and the sample period is 1998–2007. Industry Human Capital Intensity is measured by percentage of workers with college education or above for each ISIC 3-digit industry in the US in 1980. Columns (1)–(4) control for industry capital intensity, reliance on external finance, and reliance on contract enforcement. Regressions in columns (5)–(6) include all controls in column (5) of Table 4.

In columns (5)–(6) of Table 12, we report estimation results from the baseline model for the natural logarithm of the average wage of firms using the entire ASIF sample. In column (5) the estimate on the interaction between industry HC intensity and the post-2003 indicator is positive but small and insignificant. In column (6), estimates on the interactions between HC intensity and the year dummies are positive and significant for 2001–6, steadily increasing up to 2002 and gradually declining thereafter. The wage dynamics are consistent with changes in the relative supply of skilled labour. Prior to the HE expansion, skilled labour was in short supply relative to demand, and the gap may have become larger with economic development, driving up the wage of skilled labour. Given the difference in the education composition of workers, the average wage of firms in more HC-intensive industries increased more than other industries. After the large increase in the supply of skilled labour following the HE expansion the skill premium decreased, narrowing the average wage difference between more and less HC-intensive industries. This happens despite the fact that more HC-intensive industries increased their hiring of skilled labour more than other industries after 2003, as suggested by results in column (1) of Table 12.[37]

5.4. *Firms' Production Expansion*

Given the larger increases in the productivity of firms in more HC-intensive industries after the HE expansion, the scale of production of these firms could be expected to increase in relative terms. We therefore estimate (1) for various measures of the scale of firms in the full ASIF sample using the baseline specification, including as output measures total output, value added and sales revenue and, as input measures, capital stock and employment, all in natural logarithm. Estimation results are reported in online Appendix Table A5. For all measures other than employment, firms in more HC-intensive industries exhibited significantly larger increases after 2003, whereas total employment of these firms grew more slowly. These results indicate a structural shift of the overall manufacturing sector towards the more HC-intensive industries–they become not only relatively more productive but also relatively more important in the economy.

6. Conclusion

This article estimates the impact of increases in human capital on firms' productivity and the pathways by which such impacts take place, taking advantage of an exogenous surge in the college-educated labour force in China in the early 2000s that resulted from a centrally-devised, nationwide higher-education expansion in the late 1990s. We find that firms in industries that were more skilled-labour-intensive exhibited a relatively larger increase in TFP in the years after the expansion of higher education relative to previous years. This relative increase is not attributable to pre-existing trends in firm TFP or a global trend, and is robust to controlling for a number of potential confounding factors including China's accession to the WTO, reform of state-owned enterprises, and various subsamples. Meanwhile, firms in more human-capital intensive industries also showed larger increases in the adoption of advanced technologies and innovative activities, in the employment of more skilled workers and in more skilled occupations, and in their overall scale of production. These findings are consistent with the hypothesis that Chinese firms in more human-capital intensive industries initially were further away from the technology frontier due partially to the constraint of skilled labour, so that when this constraint was relaxed those firms were more able to catch up and narrow the productivity gap.

[37] The pattern of the average wage evolution is consistent with findings of Ge and Yang (2014). Using Chinese urban household survey data, they document that both high school and college wage premiums reached their peak in 2001; they argue that this is consistent with the dramatic expansion in college enrolment that started in the late 1990s and the subsequent increase in the supply of college-educated workers. See also Böhm *et al.* (2015).

One of our findings is that firms in more human-capital intensive industries showed a sharp relative increase in TFP in 2003, and it stays at the same level as in 2003 for later years. This appears to be driven by the modest relative growth of the domestic private firms. Thus, policies that target domestic private firms and facilitate their adoption of new technologies and hiring of skilled workers may be particularly important for the growth prospects of the Chinese manufacturing sector.

This study can be extended in different directions. First, the quality of college graduates may have declined over time due for example to larger classrooms, lower quality of faculty and lower innate ability of students themselves. This may potentially have had large adverse effects on the innovation capacity of the economy that are not captured in this article. Second, current data do not include firms in the service sector, so that the analysis misses an important segment of the economy that is growing rapidly and employing large numbers of college-educated workers. Bringing the service sector into the analysis would offer a fuller picture of the role human capital plays in economic growth.

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Additional Supporting Information may be found in the online version of this article:

Appendix A. Additional Figures and Tables.
Appendix B. Estimation of TFP.
Appendix C. Aggregate TFP Growth.
Appendix D. Regional Redistribution of Chinese Universities: 1955–7.
Data S1.

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