

# Computer and Information Technology, Firm Growth, and Industrial Restructuring: Evidence from Manufacturing in the People's Republic of China

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Computer and information technology is considered one of the most powerful engines of modern growth, but more empirical evidence is needed to quantify its impacts. This paper studies the role of computer and information technology in industrial restructuring by observing structural change in the manufacturing sector in the People's Republic of China using a large firm-level data set. Computer and information technology is found to boost changes in industrial structure substantially. This paper also identifies faster and higher-quality growth of firms as the underlying channel through which computer use can improve industrial structure. Firms using computers grow faster, spend more on research and development, and enjoy greater productivity.

*Keywords:* computer and information technology, firm growth, growth quality, industrial restructuring

*JEL codes:* L25, L60, O14

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## I. Introduction

In the 1950s, computers were first used by large organizations as a substitute for routine work and to augment a small fraction of nonroutine work (Bresnahan 1999). Since the advent of the personal computer in the 1980s, especially those with word processing and spreadsheet functions, the world has seen the automation of such jobs (Berger and Frey 2015). Computer technology reached a turning point during the 1980s when it became a “general purpose technology” that changed the nature of work in almost all occupations and industries (Levy and Murnane 2004, 31). Computer technology became more important as a contributor to economic growth and in reshaping economies across the world with the development of the

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World Wide Web and the growth of e-commerce throughout the 1990s. Economic development today depends more heavily than ever on computer and information technology. The United States and Germany have launched the Industrial Internet Program and Industry 4.0, respectively, to merge computer and information technology into their traditional industrial sectors. In the People's Republic of China (PRC), a report prepared by Premier Li Keqiang for the Third Session of the 12th National People's Congress in 2015, Internet +, highlighted the role of such technology in further expanding the domestic economy.

Although computer and information technology is widely considered to be one of the most powerful growth engines during the third revolution of science and technology, there is little empirical evidence on how it helps firms expand at the microlevel and contributes to economic growth at the aggregate level. For example, although Jorgenson and Vu (2005) point out that computer technology has led to an overall increase in the United States' "speed limit" for growth, empirical studies pose a challenge to this point of view. Using industry-level data, Corrado et al. (2008) and Bosworth and Triplett (2007) find that total factor productivity (TFP) grows even more slowly in industries that rely on computers. Their results, however, are in dispute; one major criticism is that TFP growth exhibits strong heterogeneity across industries and this issue has not been thoroughly addressed. It is therefore necessary to explore the effects of computer and information technology using firm-level data. Some researchers have done antecedent work in this area. Kaushik and Singh (2004) and Aker and Mbiti (2010), for example, summarize multiple ways in which the Internet can help boost firm performance in developing economies. Paunov and Rollo (2015) also identify positive impacts from Internet-enabled knowledge spillovers. Such evidence supports optimistic conclusions about the Internet's potential for improving firm performance.<sup>1</sup>

This paper provides complementary evidence for the effects of computer and information technology on firm performance and economic growth by using firm-level data from the PRC. I first focus on how computer and information technology affects firm growth. Growth rates and growth quality are both found to correlate positively with computer and information technology. Firms using more computers grow faster in terms of value added, sales, employees, and other aspects; they also spend more on research and development (R&D) and enjoy higher levels of productivity. The robustness of such findings is tested using several different methods. First, a subsample of newly opened firms is used to overcome potential reverse causality. Second, a propensity score matching procedure is

<sup>1</sup>For more details on the relationship between computer and information technology and the economy, please refer to several reviews. Berger and Frey (2015) review how computers affected labor demand and organizational practices over the course of the 20th century. Consoli, Vona, and Rentocchini (2015) review studies on how computer and information technology affects the skill structure of firms, which supplements the review of earlier studies by Autor, Katz, and Krueger (1998). Paunov and Rollo (2015) provide a brief review of multiple ways through which the Internet can help boost firm performance in developing economies, which is the study most closely related to our paper. Qiu and Bu (2013) review studies on information and communication technology in the PRC.

implemented to identify a subsample of comparable firms before regressions. Both robustness checks generate similar results to the baseline regressions. Since industrial structure adjustment plays a crucial part in economic growth, especially in developing economies, the role of computer and information technology in industrial restructuring is also studied. By aggregating the firm-level findings, it is evident that industries and regions with a high degree of computer use will grow relatively faster and industrial restructuring will occur at an accelerated pace. Computer and information technology, therefore, can boost economic growth by enhancing allocative efficiency.

This paper contributes to the literature in three ways. First, I identify the causal effects of computer and information technology on firm performance by using firm-level data and employing multiple econometric methods. This helps to rule out heterogeneity from various sources when using aggregate data, which is in line with previous studies. Second, I explore how computer and information technology improves industrial restructuring to enhance economic growth. That is, does computer and information technology boost economic growth not only through increased technological efficiency within firms and industries, but also through higher allocative efficiency across industries? Finally, I test the importance of computer and information technology in the manufacturing sector in the PRC to provide guidance for development strategies in the digital era.

The remainder of the paper is organized as follows. Section II describes the data and introduces the variables used in the empirical analysis. Section III explores the effects of computer use on firm performance, while section IV investigates how computer use at the aggregate level boosts industrial restructuring. The final section concludes.

## II. Data and Measurement

### A. Data

This study draws on data from the Chinese Industrial Enterprises Database (CIED), which is widely used in the literature in almost all aspects of the industrial sector in the PRC.<sup>2</sup> CIED is compiled from annual surveys of industrial enterprises conducted by the National Bureau of Statistics of China and comprises information on all state-owned enterprises and private firms with annual sales revenue of more than CNY5 million. The number of plants covered in the data set increased from around 165,000 in 1998 to more than 336,000 in 2007. Therefore, a large unbalanced panel is available. CIED represents approximately 90% of

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<sup>2</sup>The industrial sector in the PRC includes manufacturing, mining, and public utilities (the production and supply of electric power, gas, and water). In the PRC's National Industries Classification System (both GB/T 4754-94 and GB/T 4754-2002) at the 2-digit level, the industrial sector ranges from 6 to 46. See Holz (2013) for details on the PRC's industrial classification systems.

gross output and value added in the industrial sector in the PRC, guaranteeing the external validity of studies based on this data set (Brandt, Biesebroeck, and Zhang 2012). The information provided by CIED falls roughly into two categories: basic information (e.g., firm identity, industry and region, ownership, and skill composition) and operations information (e.g., balance sheet, cash flow statement, and income statement).<sup>3</sup>

I performed some data cleaning before engaging in the empirical analysis. First, I deleted observations for mining firms and public utilities to focus solely on manufacturing. Mining depends heavily on the distribution of natural resources, while public utilities respond to the demographic features of cities and other administrative areas. Second, I deleted observations with key variables missing. Third, since information on computer use is only reported for a single year, 2004, I lose the advantages of panel data and turn instead to cross-sectional analysis. I keep the data for 2001, 2004, and 2007, and the changes between 2004 and 2007 are employed as dependent variables to capture the impact of computer and information technology, while the changes between 2001 and 2004 are used to implement a propensity score matching procedure to address concerns about reverse causality.<sup>4</sup> Fourth, since CIED reports only nominal values for most indicators, it is necessary to transfer them into real values. The price index (at the 2-digit level) constructed by Brandt, Biesebroeck, and Zhang (2012) is used to conduct this exercise.<sup>5</sup> In addition, I winsorize all the variables by trimming 1% of observations at both the upper and lower tail of the distribution.

## B. Variables

The variable of primary interest is firm growth. I examine the effect of computer and information technology on firm growth in two dimensions: the growth rate and the quality of growth. To do so, I calculate the growth rates of employment, assets, value added, sales, and profits between 2004 and 2007. These five growth rates capture different aspects of firm growth and help eliminate the bias caused by possible measurement errors. During 2004–2007, the sales of firms in the sample more than doubled on average and both value added and profits increased by about 50%. Employment grew much more slowly during this period, implying an improvement in labor productivity. As for the quality of growth, four indicators were employed: (i) R&D intensity, (ii) share of new products in sales, (iii) TFP, and (iv) average labor productivity. The differences in these indicators between 2004 and 2007 will be used as dependent variables. R&D intensity, which is the ratio of a firm's R&D expenses to its sales, measures the firm's willingness to invest in its

<sup>3</sup>See, for example, Brandt, Biesebroeck, and Zhang (2012) for more information on CIED.

<sup>4</sup>The propensity score matching procedure is discussed in detail in the next section.

<sup>5</sup>For more details on the data, please refer to Biesebroeck (2017).

future development.<sup>6</sup> The share of new products in sales is viewed as the outcome of R&D activity. From 2004 to 2007, a typical firm spent 0.17% of its income on R&D, leading to the mean share of new products in sales growing by 0.54 percentage points. TFP is calculated using the procedure first proposed by Olley and Pakes (1996), which is now widely used in estimating firm-level TFP. Labor productivity is simply the amount of value added per worker. Table 1 shows that mean labor productivity grew by CNY63,000 (in 2004 prices) per worker.

After analyzing the effects of computer and information technology at the firm level, it follows that computer use would affect industrial structure adjustments differently across industries and regions with different intensities of computer and information technology use. I construct an index both at the city level and the city–industry level to measure industrial restructuring. At the city level, I construct the Structural Change Index (SCI), following the methodology of Brender and Drazen (2010), among others:

$$SCI_{c,04\_07} = 0.5 \times \sum_{i=1}^I |indshare_{ic,2007} - indshare_{ic,2004}| \quad (1)$$

where  $indshare_{ic,t}$  is the share of industry  $i$  for city  $c$  in year  $t$ . To eliminate bias caused by possible measurement error, I again calculate the share of each industry by using five different indicators: (i) employment, (ii) assets, (iii) value added, (iv) sales, and (v) profits. By adding up the absolute values of industry-level changes within each city, I get the SCI ( $SCI_{c,04\_07}$ ) indicating the industrial structural change between 2004 and 2007 for city  $c$ .<sup>7</sup> A larger  $SCI_{c,04\_07}$ , by definition, means a more significant adjustment in manufacturing in city  $c$  and, therefore, a huge reallocation of production factors has taken place during the review period. The different measures of SCI are quite similar to each other, implying the robustness of the measurement I used.

The SCI may signal industrial structure adjustment at the city level, but it may also cover up different trends among various industries. To address this problem, I employ an Industry Concentration Index (ICI) to track changes in each industry at the 2-digit industrial classification level. The ICI follows the methodology of Lu et al. (2013):

$$ICI_{ic,t} = \frac{indshare_{ic,t}}{indshare_{ip,t}} \quad (2)$$

Again,  $indshare_{ic,t}$  is the share of industry  $i$  for city  $c$  in year  $t$  and  $indshare_{ip,t}$  is the corresponding share for the province to which city  $c$  belongs. The share is again calculated comprising five aspects. The changes in  $ICI_{ic}$  between 2004 and

<sup>6</sup>CIED does not report R&D expenses in 2004. Therefore, R&D expenses in 2005 are used as a proxy.

<sup>7</sup>Since both the growth and decline of industry share represent industrial change, it is reasonable to use the absolute value of industry-level changes when we measure industrial structural adjustment.

Table 1. Statistics Description

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
<b>Firm Level</b>					
GR (Employment) (%) <sup>a</sup>	18,5851	27.32	90.13	-87.36	538.90
GR (Asset) (%) <sup>a</sup>	18,5811	93.20	166.59	-77.96	986.28
GR (Value added) (%) <sup>a</sup>	18,5481	56.97	277.15	-260.97	27.86
GR (Sales) (%) <sup>a</sup>	18,5471	126.76	169.28	-90.37	1039.25
GR (Profit) (%) <sup>a</sup>	18,5580	45.78	164.72	-90.15	611.64
$\Delta$ RDI <sup>b</sup>	18,5900	0.17	0.71	-1.31	4.58
$\Delta$ SNP <sup>b</sup>	18,5900	0.54	15.85	-80.01	87.07
$\Delta$ TFP <sup>b</sup>	16,4401	0.04	0.98	-3.12	2.97
$\Delta$ ALP <sup>b</sup>	18,5747	63.11	165.38	-316.61	880.00
Computer use	25,4054	8.37	12.70	0.00	77.78
Personal computer use	25,4054	7.70	12.07	0.00	74.19
Size	25,4314	9.52	1.39	6.37	13.72
Age	25,4165	8.28	9.77	0.00	50.00
Tax rate	25,0957	0.66	1.17	0.00	6.41
Leverage	25,3801	59.40	29.12	0.67	150.41
Human capital	25,4054	12.44	16.76	0.00	88.00
<b>City-Industry Level</b>					
$\Delta$ ICI (Employment) <sup>b</sup>	7,392	1.24	1.33	-2.06	6.92
$\Delta$ ICI (Asset) <sup>b</sup>	7,392	1.30	1.60	-3.55	7.38
$\Delta$ ICI (Value added) <sup>b</sup>	7,391	1.32	1.64	-2.87	7.72
$\Delta$ ICI (Sales) <sup>b</sup>	7,391	1.33	1.64	-5.11	7.96
$\Delta$ ICI (Profit) <sup>b</sup>	7,391	1.34	1.68	-4.22	8.23
<b>City Level</b>					
SCI (Employment) <sup>c</sup>	328	0.017	0.015	0.001	0.171
SCI (Asset) <sup>c</sup>	328	0.020	0.016	0.001	0.172
SCI (Value added) <sup>c</sup>	328	0.023	0.018	0.001	0.168
SCI (Sales) <sup>c</sup>	328	0.020	0.016	0.001	0.170
SCI (Profit) <sup>c</sup>	328	0.020	0.017	0.001	0.170

ALP = average labor productivity, GR = growth rate, ICI = Industry Concentration Index, RDI = research and development intensity, SCI = Structural Change Index, SNP = share of new product in sales, TFP = total factor productivity.

<sup>a</sup>indicates the growth rates of firms during 2004–2007.

<sup>b</sup>indicates the differences in corresponding variables (growth quality indicators or the ICI) during 2004–2007.

<sup>c</sup>indicates that the SCI is the change in industrial structure during 2004–2007.

Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

2007, which measure the relative growth of industry  $i$  in city  $c$ , are again used as dependent variables.

The key explanatory variable is, of course, computer and information technology. CIED reports the quantities of both computers and personal computers in each firm in 2004. Since the quantity of computers varies across firms and highly correlates with firm size, I standardize it by dividing it by employment to calculate computers per 100 workers, which is the variable primarily used in this paper. In

2004, the quantity of computers was still insufficient as there were only about eight computers per 100 workers on average. When aggregate dependent variables such as the SCI and ICI are used, I employ the mean of computers per 100 workers at the corresponding level. For example, I use the mean of computers per 100 workers within cities as the key explanatory variable for industrial structure adjustment at the city level (SCI). In other words, the mean of computers per 100 workers is applied as a proxy for the presence of computer and information technology in a particular city.

A variety of covariates are included to identify the causal effects of computer and information technology on firm growth and industrial restructuring. Firm size and age are among the first set of controls. Firm size is defined as the natural logarithm of fixed assets and age is the difference between 2004 and the year the firm opened. Tax burden is among the most important determinants of firm growth; therefore, I control for the effective tax rate, which is the ratio of income tax to sales. Financing is another crucial factor for most enterprises in the PRC (Allen, Qian, and Qian 2005) and so it is necessary to include financing constraints in our controls. I use leverage, which is the ratio of debt to assets, to measure financing constraints because greater leverage implies that a firm has easier access to finance (Rajan and Zingales 1995). Considering that human capital plays a crucial role in modern growth at both the firm and aggregate levels, especially with regard to growth rates and the quality of growth (Hatch and Dyer 2004), I control for the share of labor with at least a college degree, following Goedhuys and Sleuwaegen (2015).<sup>8</sup> Since firms vary across regions and industries, and by mode of ownership, I also include dummies to eliminate city fixed effects, industry fixed effects, and ownership fixed effects. Table 1 describes the statistics of key variables in this study.

### III. The Effects of Computer and Information Technology on Firm Growth

#### A. Specification

As our primary focus is the effect of computer and information technology on firm growth, I estimate the following equations:

$$\begin{aligned} GR_{f,2004-07} &= \alpha + \beta Computer_{f,2004} + X_{f,2004}\gamma + city_c + ind_i + own_o + u_f \\ GQ_{f,2004-07} &= \alpha + \beta Computer_{f,2004} + X_{f,2004}\gamma + city_c + ind_i + own_o + u_f \end{aligned} \quad (3)$$

where  $GR_{f,2004-07}$  is the growth rate of firm  $f$  during 2004–2007 and  $GQ_{f,2004-07}$  is the firm's quality of growth during the same period. The key explanatory variable,

<sup>8</sup>I also use share of workers holding a skill certification to measure the skill structure within firms and get similar results. These results are available upon request.

$Computer_{f,2004}$ , is the quantity of computers per 100 workers in 2004 and  $X_{f,2004}$  is a compilation of control variables. Finally,  $city_c$ ,  $ind_i$ , and  $own_o$  stand for city fixed effects, industry fixed effects, and ownership fixed effects, respectively, which are used to eliminate heterogeneity across different regions, industries, and modes of ownership. The coefficient,  $\beta$ , is of primary interest because it implies the effects of computer and information technology on firm growth. The regressions, however, are confronted with the problem of endogeneity. Specifically, a positive  $\beta$  does not necessarily imply firms using computers will grow fast; on the contrary, firms with rapid, high-quality growth in the last period may have a higher probability of buying computers. To address this problem, I will provide two sets of robustness checks by using alternative specifications in subsection III.C.

## B. Baseline Results

The baseline results are reported in Tables 2 and 3. Growth rates are used as the dependent variable in Table 2, in which the first five columns include computers per 100 workers as the key explanatory variable and the last five columns include personal computers per 100 workers. The coefficients on computer use are statistically significant at the 1% level in all five columns, implying that computer use exerts a positive impact on firm growth. To be specific, one more computer per 100 workers can increase the growth rates of employment and value added by over 1 percentage point each and increase the growth rates of assets, sales, and profits by around 0.6 percentage points each. The effect is, therefore, economically significant as well. Personal computer use as an explanatory variable in the last five columns generates coefficients with the same statistical significance and similar values, showing that the effects of personal computer use on firm growth are quite robust. An increase of one personal computer per 100 workers again improves the growth rates of both employment and value added by about 1 percentage point and the growth rates of the other indicators by around 0.5 percentage points each. To sum up, computer use has robust positive impacts on firm growth no matter how growth is measured.

As for the controls, firm size has a statistically significant negative effect on firm growth of all kinds, implying the existence of convergence as discussed in the literature (Cabral 1995, Beck et al. 2008). That is, large firms are more likely to grow more slowly than small firms. The same logic applies to firm age: younger firms grow faster than older firms. A higher tax rate correlates with a lower growth rate, which is consistent with the literature on the negative effect of a tax burden on firm growth (Shen and Chen 2017). Leverage positively correlates with growth because a higher debt ratio implies a greater ability to access financial support to fuel growth. Firms with a larger proportion of well-educated workers also grow faster, as documented by Lopez-Garcia and Puente (2012) and Arrighetti and Lasagni (2013).



Table 2. The Effects of Computer Use on Firm Growth Rates

	Employment (1)	Asset (2)	Value Added (3)	Sales (4)	Profit (5)	Employment (6)	Asset (7)	Value Added (8)	Sales (9)	Profit (10)
Computer use	1.308*** (0.023)	0.566*** (0.042)	1.098*** (0.123)	0.611*** (0.068)	0.603*** (0.067)	1.259*** (0.024)	0.533*** (0.043)	1.007*** (0.126)	0.534*** (0.070)	0.544*** (0.069)
Personal computer use										
Size	-1.079*** (0.113)	-1.382*** (0.207)	-4.189*** (0.686)	-1.387*** (0.371)	-1.299*** (0.307)	-1.058*** (0.135)	-1.365*** (0.204)	-4.178*** (0.686)	-1.329*** (0.371)	-1.239*** (0.307)
Age	-0.131*** (0.013)	-0.173*** (0.027)	-0.583*** (0.073)	-0.152*** (0.035)	-0.136*** (0.030)	-0.141*** (0.019)	-0.172*** (0.027)	-0.582*** (0.073)	-0.159*** (0.036)	-0.144*** (0.030)
Leverage	0.097*** (0.008)	0.144*** (0.014)	0.083*** (0.042)	0.328*** (0.023)	0.354*** (0.023)	0.098*** (0.008)	0.144*** (0.014)	0.084*** (0.042)	0.329*** (0.023)	0.355*** (0.023)
Tax rate	-0.041 (0.026)	-0.248*** (0.048)	-0.358** (0.142)	-0.370*** (0.078)	-0.409*** (0.077)	-0.028 (0.026)	-0.242*** (0.048)	-0.343** (0.142)	-0.361*** (0.078)	-0.400*** (0.077)
Human capital	0.306*** (0.019)	0.546*** (0.034)	1.044*** (0.100)	0.805*** (0.055)	0.786*** (0.054)	0.365*** (0.018)	0.576*** (0.034)	1.112*** (0.099)	0.849*** (0.055)	0.826*** (0.054)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185,441	185,426	185,323	185,457	185,402	185,441	185,426	185,323	185,457	185,402
R <sup>2</sup>	0.068	0.097	0.051	0.087	0.089	0.066	0.097	0.051	0.087	0.089

Notes: Robust standard errors reported in parentheses are clustered at the city level. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively. Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. “Chinese Industrial Enterprises Database.”

Table 3. The Effects of Computer Use on the Quality of Firm Growth

	R&D Intensity (1)	Share of New Products (2)	TFP (3)	Labor Productivity (4)	R&D Intensity (5)	Share of New Products (6)	TFP (7)	Labor Productivity (8)
Computer use	0.020*** (0.007)	0.010** (0.004)	0.002*** (0.000)	1.265*** (0.242)	0.022*** (0.008)	0.009** (0.004)	0.001*** (0.000)	1.250*** (0.243)
Personal computer use					0.055*** (0.001)	0.105*** (0.031)	0.011*** (0.002)	1.998*** (0.315)
Size	0.029*** (0.001)	0.130*** (0.033)	-0.041*** (0.002)	-2.150*** (0.332)	0.029*** (0.001)	0.130*** (0.033)	-0.041*** (0.002)	-2.144*** (0.332)
Age	0.001*** (0.000)	0.016* (0.009)	0.000 (0.000)	0.084*** (0.014)	0.001*** (0.000)	0.002 (0.003)	-0.000 (0.000)	0.084*** (0.014)
Leverage	-0.042*** (0.012)	-0.612** (0.289)	-0.160*** (0.022)	-43.737*** (2.915)	-0.048*** (0.012)	-0.596** (0.289)	-0.161*** (0.022)	-44.047*** (2.914)
Tax rate	0.005*** (0.000)	0.013*** (0.003)	0.007*** (0.000)	0.424*** (0.034)	0.005*** (0.000)	0.014*** (0.003)	0.005*** (0.000)	0.438*** (0.034)
Human capital								
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185,457	185,457	164,052	185,343	185,457	185,457	164,052	185,343
R <sup>2</sup>	0.164	0.022	0.065	0.089	0.164	0.022	0.065	0.089

R&D = research and development, TFP = total factor productivity.  
 Notes: Robust standard errors reported in parentheses are clustered at the city level. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively.  
 Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

Table 3 examines the effects of computer and information technology on the quality of firm growth. Again, I use the number of computers and personal computers per 100 workers as key explanatory variables in the two panels. Both variables have a positive impact on the quality of growth and most of the coefficients on them are statistically significant at the 1% level. Specifically, one more computer per 100 workers will increase R&D intensity by 0.02 percentage points, or over one-tenth of the mean of the R&D intensity change (see Table 1 for the mean of the indicators of growth quality). The share of new products increases by 0.01 percentage points, or approximately 2% of the mean, with an additional computer; TFP increases by 0.002 percentage points (5% of the mean); and labor productivity increases by 1.265 percentage points per worker (3% of the mean). Therefore, computer and information technology not only boosts firm growth as shown in Table 2, but it also improves the quality of growth.

A glance at the control variables gives a slightly different picture. Firm size has a significantly positive effect on the quality of growth. Although large firms grow more slowly, they put more emphasis on the quality of growth such as R&D expenditure and productivity improvements. Younger firms spend less on R&D and sell fewer new products than older firms, but they typically are more productive. Tax rates and leverage have similar effects on the quality of growth as they do on the growth rate. Access to finance increases R&D intensity and improves labor productivity significantly, while a lighter tax burden is beneficial for all measurements of growth quality. As in Table 2, an increase in human capital has a positive impact on the quality of growth in the next period.

### C. Robustness Checks

Cross-sectional analysis can suffer from endogeneity problems due to reverse causality. The positive correlation between computer use and growth does not necessarily prove the causal effect of computer and information technology on firm growth. On the contrary, the positive correlation may stem from the fact that firms with higher growth rates are more inclined to adopt computer and information technology. To address this problem, I conducted two sets of robustness checks.

The first set restricts regressions to a subsample of firms that were newly established in 2004.<sup>9</sup> Reverse causality is no longer a concern because all firms in this subsample commenced operations in 2004 and therefore have no prior history. The empirical results based on this subsample are reported in Tables 4 and 5, with growth rates and quality of growth as the dependent variables, respectively.

Table 4 investigates the relationship between computer and information technology and different measurements of growth. All coefficients on computer use (Panel A) and personal computer use (Panel B) are statistically significant

<sup>9</sup>CIED data include the first year of operation for each firm.

Table 4. The Effects of Computer Use on Growth among Newly Opened Firms

	Employment (1)	Asset (2)	Value Added (3)	Sales (4)	Profit (5)
Panel A					
Computer use	1.943*** (0.139)	0.757*** (0.266)	2.118*** (0.480)	0.208*** (0.044)	0.708*** (0.146)
Observations	9,676	9,674	9,665	9,676	9,671
R <sup>2</sup>	0.117	0.152	0.105	0.152	0.151
Panel B					
Personal computer use	1.971*** (0.145)	0.876*** (0.278)	2.102*** (0.479)	0.188*** (0.044)	0.895*** (0.173)
Observations	9,676	9,674	9,665	9,676	9,671
R <sup>2</sup>	0.116	0.153	0.105	0.152	0.151
Control variables	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Ownership fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors reported in parentheses are clustered at the city level. The coefficients and standard errors for control variables are not presented to save space. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively.

Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

Table 5. The Effects of Computer Use on the Quality of Growth among Newly Opened Firms

	R&D Intensity (1)	Share of New Products (2)	TFP (3)	Labor Productivity (4)
Panel A				
Computer use	0.014** (0.007)	0.008** (0.005)	0.002** (0.001)	1.677*** (0.338)
Observations	9,676	9,676	8,371	9,675
R <sup>2</sup>	0.158	0.088	0.133	0.140
Panel B				
Personal computer use	0.017** (0.009)	0.007*** (0.002)	0.003* (0.002)	1.590** (0.349)
Observations	9,676	9,676	8,371	9,675
R <sup>2</sup>	0.161	0.088	0.133	0.140
Control variables	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Ownership fixed effects	Yes	Yes	Yes	Yes

R&D = research and development, TFP = total factor productivity.

Notes: Robust standard errors reported in parentheses are clustered at the city level. The coefficients and standard errors for control variables are not presented to save space. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively.

Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

and positive, implying that the causal effect of (personal) computer use on firm growth is still robust. The difference lies in magnitude, however, as there are larger coefficients for the new firm subsample on all growth measurements except for sales. When computer use rises by one computer per 100 workers, the growth rates of employment and value added increase by around 2 percentage points each and the growth rates of assets and profits increase by about 0.7 percentage points each. This is partly because the regressions using the full sample suffer from bias and partly because newly established firms grow more rapidly than older ones (Table 3). Personal computer use has similar effects on the quality of growth measurements as shown in Panel B.

The effects of computer and information technology on the quality of growth among newly opened firms are shown in Table 5, with computer use in Panel A and personal computer use in Panel B. The effects on R&D expenditure and share of new products are lower than those observed for the full sample in Table 3. A plausible explanation is that new firms rely less on innovation. Thus, an increase of 0.014 percentage points in R&D intensity and 0.008 percentage points in the share of new products are still significant economically, considering that the mean growth of R&D intensity and the share of new products for new firms are only 0.15 percentage points and 0.36 percentage points, respectively. Table 5 shows the relatively larger effects of personal computer use on productivity, implying that new firms benefit even more from personal computer use.

In the subsample of new firms, personal computer use exerts a significantly positive influence on growth rates and the quality of growth. Therefore, the results shown in Tables 4 and 5 further alleviate concerns about reverse causality.

When attempting to identify the correlation between computer and information technology and growth rates and growth quality as a causality relationship, the heterogeneity of firms is an important factor. Specifically, there may be some heterogeneous features that determine a firm's computer use on one hand and impact its future development on the other. Examples of such heterogeneous features include a firm's prior growth rates and the quality indicators of growth. By using only newly opened firms, I remove some of the possible biases resulting from these sources of heterogeneity. As a second robustness check, I use a propensity score matching technique to address potential bias stemming from other kinds of heterogeneity. If the correlation between computer use and firm growth rates and growth quality might only reflect the impact of heterogeneous features, comparing firms that share similar features with each other is necessary. The propensity score matching technique, first proposed by Rosenbaum and Rubin (1983), provides a standard procedure to choose firms with features in common to give a matched sample in which observations are similar in terms of these specified features.

Table 6 presents the results for propensity score matching. The left panel reports the results of a probit regression in which the dependent variable is a dummy

Table 6. Propensity Score Matching Regression and Postestimation Test

Results of Probit Regression		Test for Balance			
		Sample	Mean		Absolute Value of Difference
Variable	Coefficient (Standard Error)		Control Group	Treatment Group	
Profit rate	0.011***	BM	8.31	9.97	1.66***
	(0.003)	AM	8.15	8.54	0.40
Grow rate of profit	0.125	BM	86.69	97.89	11.20***
	(0.175)	AM	96.63	98.60	1.98
Size	0.270***	BM	8.74	9.62	0.88**
	(0.006)	AM	9.08	9.42	0.34*
Age	-0.002***	BM	10.17	8.04	2.13**
	(0.001)	AM	8.47	7.97	0.49
Tax rate	-0.031***	BM	0.55	0.66	0.11**
	(0.006)	AM	0.61	0.67	0.06
Leverage	0.001***	BM	55.11	59.92	4.82***
	(0.000)	AM	57.64	58.85	1.21
Human capital	0.440***	BM	9.02	12.86	3.84***
	(0.040)	AM	10.48	12.78	2.31*
Female share	0.387***	BM	33.50	36.25	2.75**
	(0.057)	AM	35.18	36.21	1.03
Ownership dummies	Yes				
City dummies	Yes				
Industry dummies	Yes				
Observations	250,799				
Pseudo R <sup>2</sup>	0.209				

AM = after matching sample, BM = before matching sample.

Notes: The dependent variable in the left panel is a dummy that measures whether a firm has a computer. The right panel shows results from testing the difference between two groups (AM and BM). The p-value (indicated by stars) in the last column is for the null hypothesis, which states that there is no difference between the two groups. The coefficients and standard errors for dummies are not presented to save space. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively.

Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

to measure whether a firm owns computer(s) or not. The primary determinants for computer use include a firm's profits and annual average growth rate during 2001–2004, lagged firm size, age, tax rate, leverage, and the employment share of skilled workers (workers with at least a college education) and female workers. I also control for the mode of ownership, urban versus rural areas, and 2-digit industry fixed effects to eliminate the impacts of unobservable heterogeneity. Most of the coefficients are statistically significant. Typically, firms with higher profits and growth rates, lower tax rates, and more leverage are more likely to adopt computer and information technology. Larger and younger firms are also inclined to adopt computer and information technology. In addition, computer use is highly correlated with human capital and the share of female workers, which is consistent with the capital–skill complementarity hypothesis (Goldin and Katz 1998) and

Table 7. The Effects of Computer Use on Firm Growth: Matched Sample

	Employment (1)	Asset (2)	Value Added (3)	Sales (4)	Profit (5)
Panel A					
Computer use	1.201** (0.499)	0.553** (0.259)	1.690*** (0.638)	0.303*** (0.040)	0.375*** (0.145)
Observations	128,421	128,418	128,332	128,428	128,392
R <sup>2</sup>	0.088	0.080	0.068	0.098	0.111
Panel B					
Personal computer use	1.202** (0.499)	0.554*** (0.206)	1.681*** (0.638)	0.257*** (0.027)	0.391*** (0.097)
Observations	128,421	128,418	128,332	128,428	128,392
R <sup>2</sup>	0.088	0.080	0.068	0.098	0.111
Control variables	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Ownership fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors reported in parentheses are clustered at the city level. The coefficients and standard errors for control variables are not presented to save space. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively.

Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

the skill-biased technical progress hypothesis (Autor, Katz, and Krueger 1998; Acemoglu 2003).

The right panel of Table 6 shows results for a test of the difference between a control group (firms without computers) and a treatment group (firms using computers) both before and after the propensity score matching. The two groups are much more similar to each other after the matching. For example, before matching the mean profit rate is 8.31% for firms without a computer and 9.97% for firms with a computer. The difference is statistically significant at the 1% level. In the matched sample, the mean profit rates of the two groups are 8.15% and 8.54%, respectively, and the difference is no longer significant, indicating that the control group and treatment group have become comparable in terms of profit rates. The same logic applies to other variables, which together make the two groups comparable in almost all important dimensions.

I can now reestimate equation (3) using the matched sample from Table 6. The results are presented in Tables 7 and 8.<sup>10</sup> Table 7 tests the correlation between

<sup>10</sup>The usual propensity score matching results compare firms with and without computers rather than estimating the effect of computer intensity in a firm. In this paper, however, the propensity score matching method is used in a slightly different way. In the first step, I run a probit regression to get a matched subsample, which is a standard propensity score matching procedure. In the second step, I use the matched sample to run regressions of firm performance on computer intensity rather than a dummy for computer use. I view the coefficient as the effect of computer intensity on a firm. The adjusted propensity score matching in this paper is right only when the following assumption is satisfied: there is a difference between firms with computers and those without; but for firms with more computers and those with less computers, the difference in other aspects is not crucial. I thank an anonymous referee for reminding me of this point.

Table 8. The Effects of Computer Use on the Quality of Firm Growth: Matched Sample

	R&D Intensity (1)	Share of New Products (2)	TFP (3)	Labor Productivity (4)
Panel A				
Computer use	0.038*** (0.014)	0.012** (0.006)	0.003*** (0.001)	1.570*** (0.253)
Observations	128,428	128,428	111,862	128,334
R <sup>2</sup>	0.176	0.051	0.091	0.114
Panel B				
Personal computer use	0.039*** (0.013)	0.011** (0.005)	0.003*** (0.001)	1.572*** (0.256)
Observations	128,428	128,428	111,862	128,334
R <sup>2</sup>	0.176	0.051	0.091	0.114
Control variables	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Ownership fixed effects	Yes	Yes	Yes	Yes

R&D = research and development, TFP = total factor productivity.

Notes: Robust standard errors reported in parentheses are clustered at the city level. The coefficients and standard errors for control variables are not presented to save space. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively.

Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

computer use and the growth rates of matched firms. Most of the coefficients are again statistically significant at the 1% level, verifying the robust causality relationship. The magnitude of the coefficients in both panels A and B are smaller than when using the full sample (except for column 3). This is partly because of a potential upward bias from an estimation of the full sample and partly because the firms in the matched sample grow more slowly on average. The economic significance does not change much. For example, regarding the growth rate of employment, one more computer per 100 workers contributes an additional 1.2 percentage points to the growth rate, or 5% of the mean (mean growth rate of employment for the matched sample is 23.8%). This is slightly larger than the 4.8% recorded in column 1 in Table 3.

When I test the causal effect of computer and information technology on the quality of growth using a matched sample in Table 8, I get slightly larger coefficients compared with those in Table 3. The economic significance is also larger because the mean quality of growth in the matched sample is lower. For example, one more computer per 100 workers causes a 0.01 percentage point increase in the share of new products, accounting for less than 2% of its mean in the full sample (Tables 1, 3). For the matched sample, the same increase in computer use contributes to 3% of its mean share of new products, which is 0.41 percentage points. The estimation from the full sample suffers little, if any, downward bias.



#### IV. The Effects of Computer and Information Technology on Industrial Restructuring

The previous section provided evidence that computer and information technology boosts growth rates and improves the quality of growth for industrial firms. By aggregating the firm-level data, it can be shown that industries and regions with high levels of computer use will grow more rapidly and industrial restructuring will accelerate in comparison to other industries and regions. Since industrial structure adjustment plays a crucial role in economic growth, especially in developing economies (Chenery et al. 1986, Lin 2009), I empirically test the role of computer use in two steps.

First, I examine the effects of computer and information technology on industry growth at the city–industry level. I estimate equation (4) as follows:

$$ICI_{ic,04\_07} = \alpha + \beta Computer_{ic,2004} + X_{ic,2004}\gamma + city_c + ind_i + own_o + u_{ic} \quad (4)$$

where the change in the ICI for industry  $i$  in city  $c$  during 2004–2007 ( $ICI_{ic,04\_07}$ ) is the dependent variable. The key explanatory variable is the mean of (personal) computers per 100 workers within the city–industry cluster. As for the control variables, I aggregate the firm-level controls at the city–industry level and use the means of firm size, age, tax rate, leverage, and human capital as controls.<sup>11</sup> In addition, I control for market structure by using a Herfindahl–Hirschman Index, control for government power by using the share of state-owned enterprises, and control for openness of the city–industry cluster by using mean foreign direct investment shares.

The results presented in Table 9 support the hypothesis that industries using more computers will grow faster relative to their peers in the same city. Almost all coefficients on computer use are positive and statistically significant at the 1% level, except when measuring the ICI using employment. A reasonable explanation for this involves the relationship between labor and computer technology as production factors. On one hand, computers improve productivity and growth, encouraging firms to hire more labor. This scale effect, as it is called in standard labor economics, is consistent with what I find at the firm level as shown in Tables 2, 4, and 7. On the other hand, the substitution effect also has an impact; that is, computers work well for some routine tasks and can crowd out labor (Acemoglu 2002). Because the scale effect and substitution effect work in opposite directions, an aggregation at the city–industry level generates less significantly positive coefficients. For the other measures of the ICI, I can safely conclude that computer and information technology plays a huge role in city–industry growth. Furthermore, the coefficients are very similar to each other. Taking the ICI of assets, for example, one more

<sup>11</sup>The share of labor with a college degree or above is again used as a proxy for human capital.

Table 9. The Effects of Computer Use on the Industry Concentration Index

	Employment (1)	Asset (2)	Value Added (3)	Sales (4)	Profit (5)
Panel A					
Computer use	0.009* (0.005)	0.033*** (0.004)	0.031*** (0.004)	0.031*** (0.004)	0.031*** (0.004)
Observations	6,358	6,358	6,358	6,358	6,358
R <sup>2</sup>	0.305	0.265	0.265	0.272	0.267
Panel B					
Personal computer use	0.010** (0.005)	0.037*** (0.004)	0.037*** (0.005)	0.036*** (0.005)	0.036*** (0.005)
Observations	6,358	6,358	6,358	6,358	6,358
R <sup>2</sup>	0.305	0.264	0.265	0.271	0.267
Control variables	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Ownership fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parentheses. The coefficients and standard errors for control variables are not presented to save space. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively.

Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

computer per 100 workers boosts the ICI by over 2%. The coefficients on the control variables are also reasonable and there is no reason to explain them again.

The empirical analysis at the city–industry level implies that the more industries adopt computer and information technology, the faster they grow relative to other industries within the same city. Differences in the use of computer and information technology across industries result in uneven growth rates, which in turn lead to industrial restructuring within manufacturing. To test this hypothesis, I run regressions of the SCI of all kinds on computer use at the city level. In addition to the control variables of city–industry level regressions, I further control for more city-level variables, including gross domestic product per capita, population density, and the employment shares of secondary industry and services. All of these covariates come from the China City Statistical Yearbook (National Bureau of Statistics of China 2004).

$$SCI_{c,04\_07} = \alpha + \beta Computer_{c,2004} + X_{c,2004}\gamma + prov_p + u_c \quad (5)$$

Table 10 presents results for estimating equation (5). Again, I use two panels to mark the difference between computer and personal computer use, which are measured as the combined number of computers per 100 workers within a city. In brief, computer use is highly correlated with structural changes within manufacturing, no matter which index is used. Furthermore, the coefficients are extremely close to each other, ranging between 0.0027 and 0.0029 in Panel A and between 0.0060 and 0.0096 in Panel B. This means that an additional computer per 100 workers can boost

Table 10. The Effects of Computer Use on the Structural Change Index

	Employment (1)	Asset (2)	Value Added (3)	Sales (4)	Profit (5)
Panel A					
Computer use	0.0028*** (0.0001)	0.0028*** (0.0002)	0.0027*** (0.0002)	0.0028*** (0.0002)	0.0029*** (0.0002)
Observations	275	275	275	275	275
R <sup>2</sup>	0.620	0.547	0.460	0.566	0.562
Panel B					
Personal computer use	0.0096*** (0.0027)	0.0078*** (0.0029)	0.0060* (0.0033)	0.0080*** (0.0029)	0.0082*** (0.0029)
Observations	275	275	275	275	275
R <sup>2</sup>	0.576	0.501	0.368	0.494	0.494
Control variables	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parentheses. The coefficients and standard errors for control variables are not presented to save space. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% level, respectively.

Source: Author's calculations based on National Bureau of Statistics of China, 1998–2008. "Chinese Industrial Enterprises Database."

structural change in employment by 0.0028 percentage points, or approximately 14% of its mean, which has huge economic implications for cities that need resource allocation to boost growth.<sup>12</sup> The effect of personal computer is even larger. In addition, the direction of the reallocation of production factors shifts resources from low-efficient industries toward industries with more R&D activity and higher productivity, according to the results in the previous section. In summary, the more computers that are used in a city, the faster structural change will occur.

## V. Conclusions

While people regularly enjoy the benefits brought about by computer and information technology, its economic effects have not been fully explored. To narrow this gap in the literature, this paper first studies the effects of computer and information technology on firm growth and industrial change in the manufacturing sector in the PRC. Using data from CIED, I empirically examine the correlation between computer use and firm performance. The main finding is that firm growth—both in terms of the growth rate and growth quality—heavily benefits from computer and information technology. This finding is robust when I use different measures and restrict the regression to newly opened firms or a matched sample to rule out possible disturbances caused by heterogeneous features. As a straightforward extrapolation, industries with a high level of computer use grow faster and cities with a high level of computer use also experience more rapid

<sup>12</sup>When other indicators are used to measure structural change, the economic effects become smaller because the means of these other indicators are relatively larger. Nevertheless, one more computer per 100 workers can increase the SCI by over 10%.

industrial structural change. That is, computer and information technology has been observed to accelerate restructuring in the manufacturing sector in the PRC.

The findings in this paper have both theoretical importance and policy implications. In theory, this paper points out two channels through which computer and information technology can contribute to economic development. At the micro level, computer and information technology boosts firm growth and improves the quality of growth in terms of increased innovation and higher productivity. At the macro level, computer and information technology accelerates industrial restructuring and helps production resources flow from low-productivity industries to high-productivity ones, which in turn enhances average productivity. As for policy implications, the empirical findings in this paper underlie the PRC's development strategy as outlined in the New Four Modernizations, especially the interaction between industrialization and informatization.<sup>13</sup> Computer and information technology have impacted and changed many sectors, including manufacturing, during the current digital era. This paper provides evidence of the positive effects of informatization on industrialization and offers guidance for governments on simultaneously boosting both industrialization and informatization.

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<sup>13</sup>The New Four Modernizations strategy was first proposed at the 18th National Party Congress in November 2012. The strategy underlines new-type industrialization, informatization, urbanization, and agricultural modernization with Chinese characteristics.

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