Induced Innovation and Labor Productivity in China

Belton M. Fleisher
fleisher.1@osu.edu
Ohio State University, & Hunan University Center for Economics, Finance, and Management Studies

William H. McGuire
wmcguire@uw.edu
University of Washington Tacoma

Xiaojun Wang
xiaojun@hawaii.edu
University of Hawaii

Min Qiang Zhao
kent_zhao@xmu.edu.cn
WISE, Xiamen University

Abstract

We investigate the effect of factor-price-induced innovation on labor-productivity growth in China. The connection between rising input prices and technological innovation has been addressed in the economics literature at least since J. R. Hicks' *Theory of Wages* (1932) and is very important to China as rising labor costs impact its competitiveness in the world marketplace. We propose a theoretical model linking changes in the labor share of output to changes in the price of labor (the wage), and the availability of physical capital. Importantly, we derive testable hypotheses to distinguish induced innovation from standard substitution of capital for labor under fixed technology. Our empirical results support the hypothesis that wage-induced technology change has influenced productivity growth in China, at least in the decade of the 1990s, but less so or not at all after the middle of the next decade.

JEL Codes O30; D22; D24; D33

Keywords: induced innovation; labor productivity growth; China

1. Introduction

We address the question of whether rising labor costs in formerly low-wage China have stimulated labor saving technological innovation, beyond what would normally occur through factor substitution under fixed technology, either through domestic innovative activity or indirectly through adapting labor-saving technology already available at the world technology frontier. Thus we complement research that assumes technical change to be exogenous, as in Wei, Xie, and Zhang (2017), Molero-Simarro (2017), Ge and Yang (2014), Bai and Qian (2010) and many other well-known publications they cite. Evidence of China's achievements in innovation as reflected in research and development (R&D) investments and in successfully applying for patents is addressed in a number of studies, two noteworthy examples being Hu and Jefferson (2009) and Wei, Xie, and Zhang (2017). Our approach seeks direct evidence of successful innovation in response to the rising scarcity of labor by examining the link between rising wages and labor productivity growth.

The connection between rising input prices and technological innovation has been addressed in the economics literature at least since J. R. Hicks' *Theory of Wages* (1932). Following Acemoglu (2010) and Acemoglu and Autor (2011), we propose a model with endogenous technology adoption based on the intensive form of the Cobb-Douglas production function. From this base we derive regression equations that allow us to test hypotheses that labor productivity growth has exceeded the amount that can be attributed to factor substitution under fixed production parameters. Our empirical results provide moderate support for the hypothesis that wage-induced technology change increased labor productivity growth in China, especially during the 1990s.

Wage-induced innovation is a critically important issue not only for China's continued economic growth, but also for the employment impact of the expansion of manufacturing to lower-wage economies. In our model, adapted from Acemoglu (2010), innovation in response to rising wages will be laborsaving --raising the production elasticity of capital and the output per unit of labor. This implies that employment gains will be muted as manufacturing moves to "low wage" regions and countries. The industrial explosion that turned China into "workshop of the world" (Gao, 2012) has led other nations to hope that the availability of low-cost labor will also lead to employment booms as manufacturers continue to maintain international competitiveness. However, these aspirations have often been disappointed, because the employment impact of expanding output is continually damped by rising productivity (Zhong, 2015). This study of induced technology change may shed some light on this phenomenon, assuming the labor-saving innovations are portable across national borders.

The next section introduces our data sources and explains some of the basic trends observed in summary statistics. Section 3 presents our theoretical model and estimation results, Section 4 very briefly discusses our results in connection with other research on innovation in China, and Section 5 concludes.

2. Data

Our two principal sources of data are official provincial employment and output statistics and the widely used Large and Medium Enterprises (LME) data base[1]. Provincial secondary-industry real capital data from the same data used in Wu (2016) have kindly been provided by the author, Yanrui Wu. We analyze both provincial and the LME data to get a more complete picture of induced innovation in China's recent past. The provincial data are available over a longer time period. The LME data are predominantly secondary industry and enable us to match employment, wage, and capital-stock data at the individual firm level. They also allow us to account for differences in the propensity to innovate between larger and smaller firms, the importance of which is emphasized by An, (2017). Estimation results derived from the LME data use samples subjected to a two-tail 7% trim (14% total) of extreme values based on total wage payments divided by value added[2]. Tables 1a and 1b present the summary statistics of our basic variables. As indicated in table 1b, we distinguish three subsamples within the LME data: all firms; medium plus large firms; and large firms, based on designations provided in the data source.

We can find some preliminary evidence of induced technological change by comparing the growth of labor productivity (Y/L) to the growth of the real wages. Under fixed technology with a Cobb-Douglas production function, the growth rate of labor productivity should be equal to real wage growth[3]. Figure 1 shows the growth of real wages between 1983 and 2012. It

[1] The number of enterprises included in the LME data constituted approximately 3.1% of the registered firms in China based on data reported by Wei, Xie, & Zhang (2017). They are primarily located in secondary industry and results are quite robust to the exclusion of all enterprises not located in this industrial category. Changes in sample definitions and variables measured limit our ability to use the full time range of available LME surveys.

[2] Our estimation results are quite robust to the trimming of implausibly extreme values.

[3] The model and derivations derived from it are based on the assumption of unitary labor:capital elasticity of substitution. This assumption is often used as a basis for analysis of technical change in theoretical analysis (e.g.,

contains two series for China's real wage growth, one of them normalized to account for the substantial increase in the proportion of workers with at least minimum junior middle school education. In both series, real wage growth increased abruptly in the late-1990s and remained substantially higher than in the preceding ten years through at least 2012[4]. Figure 2 illustrates the level and annual growth of labor productivity in secondary industry, and shows that labor productivity rose continuously throughout the entire period 1985-2011. The relatively high rate of secondary-industry productivity growth illustrated in figure 2 is also associated with the continued rapid growth of the ratio of secondary industry physical capital to labor (K:L) shown in figure 3.

Figure 4 panels A and B reveal that labor productivity growth exceeded real wage growth in most provinces and on average between 1991 and 2001 but not in the ensuing decade. We summarize these data in the aggregate with a 3-year centered moving average in figure 4 panel C, which again shows that average labor productivity growth exceed average real wage growth in the decade preceding the year 2000, while the inequality is reversed in the following 10 years.

Panel D of figure 4 illustrates the time path of $\Delta Log(Y/L)$- $\Delta LogW$ for the "Large" subsample series of LME firms (constituting about 2.5% of the total sample firms but nearly 60% of total physical capital)[5] and the path for the entire ("All") sample. Among the "Large" subsample, productivity growth exceeds wage growth through the year 2003 followed by a sharp decline through 2006 through 2007. For the sample including all enterprises, annual real-wage growth exceeds that of labor productivity throughout almost the entire period 1999-2007, with only a slight jump to positive territory during the second full year following China's WTO accession.

Gancia, Müller, and Zilibotti, 2013, and many others). Ge and Yang (2014) report elasticities of substitution between labor and physical capital that exceed 1.0 for high-skilled labor and 2.0 for low-skilled labor based on analysis of economy-wide GDP data over the state and nonstate sectors. Bai and Qian (2010) report that based on an important industrial firm census conducted by the China Statistic Bureau over a time period roughly matching the period covered by our LME data, they find that the capital:labor elasteicity of substitution does not differ significantly from1. Mallick (2012) provides individual estimates for 90 countries over the period 1950-2000; the vast majority of substitution elasticities are significantly less than 1, and that for China is 0.55 with standard error of 0.22. We further discuss implications for our hypothesis tests in the Conclusion.

[4] The impact of accelerating wage growth in China has led to an immense literature that we cannot fully cite here. We note the insights in Yang, Chen, & Monarch (2010) and those in the collection of papers on whether China has passed the Lewis Turning Point in *China Economic Review* (2011).

[5] The LME data are available to us in consistent form from 1998 through 2007 for all sampled firms and from 1996 through 2007 for "Large" and "Medium and Large" subsets of the data.,

In summary, our overview of both provincial aggregate- and firm-level micro data suggest wage-induced technology change during the reform period in China, at least through the early 2000s. Next we develop a theoretical model and derive testable hypotheses that will allow for a more rigorous examination of the induced innovation hypothesis.

3. Theoretical Model and Empirical Results.

We base our formal estimates on theoretical concepts developed by Acemoglu (2010) and included in Acemoglu and Autor (2011). Our adaptation of the conditions under which labor scarcity encourages technological advances is summarized briefly here and presented in detail in the Appendix.

We specify the production function

$$Y = \alpha^{-\alpha}(1-\alpha)^{-1}(K^{\theta}L^{1-\theta})^{\alpha} q(\theta)^{1-\alpha} \tag{1}$$

where $\alpha^{-\alpha}(1-\alpha)^{-1}$ is a convenient normalization further elaborated in the Appendix. We take the availability of physical capital as exogenously determined ($K=\overline{K}$). A technology θ is created at a cost $C(\theta)$. The unit production cost of the intermediate good ($q(\theta)$) embodying this technology is assumed to be denominated in units of the final good, whose price is normalized to 1.

To provide an adequate test of hypotheses related to wage-induced technology change, we add a factor-neutral productivity term (total factor productivity--TFP) A to (1):

$$Y = A\alpha^{-\alpha}(1-\alpha)^{-1}(K^{\theta}L^{1-\theta})^{\alpha} q(\theta)^{1-\alpha} \tag{2}$$

and in our empirical work we rely primarily on the production function in intensive form:

$$\begin{aligned} \frac{Y}{L} &= \frac{A\alpha^{-\alpha}\left(1-\alpha\right)^{-1}\left(\overline{K}^{\theta}L^{1-\theta}\right)^{\alpha}\left(A^{1/\alpha}\alpha^{-1}\left(\overline{K}^{\theta}L^{1-\theta}\right)\right)^{1-\alpha}}{L} \\ &= A^{1/\alpha}\alpha^{-1}\left(1-\alpha\right)^{-1}\left(\frac{\overline{K}}{L}\right)^{\theta} \end{aligned} \tag{3}$$

In the Appendix, we show that, we can write (3) in terms of the real wage W, obtaining

$$\frac{Y}{L} = \alpha^{-1}\left(1-\alpha\right)^{-1}\frac{W\left(1-\alpha\right)}{1-\theta} = \frac{1}{\alpha(1-\theta)}W \tag{4}$$

Defining $\phi = \ln\left(\frac{1}{\alpha(1-\theta)}\right)$, dividing both sides of (4) by W, and taking logs, we can characterize the behavior of θ over time as:

$$\ln\left(\frac{Y_{it}}{L_{it}}\frac{1}{W_{it}}\right) = \phi_t + \eta_i + \varepsilon_{it} \qquad \textbf{(4a)}$$

where ϕ_t and η_i denote year and provincial dummies, respectively, and $\frac{1}{e^{\phi_t - \phi_0}} = \frac{1-\theta_t}{1-\theta_0}$.

<u>Hypothesis i</u>: Based on equation (4a), under induced technological change, θ_t is greater than θ_0 implying that the ratio $\frac{1-\theta_t}{1-\theta_0}$ should be less than 1,

Empirical Results for Hypothesis (i).

We estimate equation (4a) using provincial data, reporting the results in table 2 and in figure 5, panel A, along with their 95% confidence intervals. We also estimate the model in first-difference form. Results for a first-difference specification are reported in the right-hand columns of table 2 and in figure 5, panel B. The first-difference specification helps account for systematic errors in the measurement of wages resulting from the omission of casual workers in our data.

Both the level and first-difference estimates tell a similar story. The ratio $\frac{1-\theta_t}{1-\theta_0}$ falls (θ_t rises relative to θ_0) abruptly in 1986 and 1987, maintaining its path through the end of the 1990s and then leveling off (in the first-difference specification) through the end of the next decade. The 95% confidence interval for the first-difference estimation broadens considerably in the post-2000 decade, possibly encompassing the slight increase in $\frac{1-\theta_t}{1-\theta_0}$ in the level estimation. These results generally support the induced technological change hypothesis. Consistent with the data illustrated in figure 4, the decade of the 1990s exhibits greater evidence of price-induced technology change.

Figure 5 panel C reports the estimated values of $\frac{1-\theta_t}{1-\theta_0}$ over time, by region. The time paths track quite closely until the end of the 1990s, when they diverge in both trends and levels. Only the Northeast region maintains a level or slightly declining track of $\frac{1-\theta_t}{1-\theta_0}$ (increasing $\frac{\theta_t}{\theta_0}$) after 1999. We conjecture that the Northeast's greater productivity relative to wage growth from the late 1990s through the first decade of the 21st century is attributable to the downsizing and reorganization of its large SOE sectors that involved laying off redundant workers (*xiagang*), as discussed above. The path of $\frac{1-\theta_t}{1-\theta_0}$ in the far west region rises above those of the other three provincial groups after 1995

Regression results for equation (4a) based on the subsample of the Large enterprises in the LME data are reported in figure 5 panel D and in table 2a column (1), with the base year set at 1996, the first sample year available to us. For comparison, in table 2a column (2) we normalize the provincial regression results from table (1) to 1996 = 1. The implications for induced technology change share the same trend (declining value of $\frac{1-\theta_t}{1-\theta_0}$ indicating a positive trajectory for $\frac{\theta_t}{\theta_0}$) between 1996 and 2001, but the trend is much more pronounced for the LME sample of Large enterprises, consistent with the largest enterprises being more innovative than the average. After the year 2001, both series indicate a weakening of induced technology change, but more so among the set of firms represented in the provincial data. The provincial data reflect the behavior of firms of all sizes, and thus the evidence of a lower productivity growth relative to wage growth reflected in the provincial data is not surprising.

Methodology: Controlling for Omitted Variables. Estimation of induced technological change through equation (4a) may be biased by omission of variables correlated with both the real wage and factor-neutral productivity (TFP) growth and/or the availability of physical capital *K*. To deal with these two issues, we take logs of (4) and, adding the date and location identifier, we obtain the following approximations:

$$\ln\left(\frac{Y}{L}\right)_{it} = \alpha_{it} + \beta \ln W_{it} + \delta \ln \bar{K}_{it} + \varepsilon_{it} \qquad \textbf{(5).}$$

Under endogenous technical change, $\frac{\partial\theta}{\partial\bar{K}} > 0$ and $\frac{\partial\theta}{\partial W} > 0$. Thus, we test the following hypotheses:

***Hypothesis ii*:** β >1 (indicating $\frac{\partial\theta}{\partial W} > 0$)

***Hypothesis iii*:** δ >0 (indicating $\frac{\partial\theta}{\partial\bar{K}} > 0$)

Empirical Results for Hypotheses (ii)-(iii): Tests with provincial data.[6]

We estimate equation (5) with year- and regional fixed effects as well as region-specific time trends to capture exogenous shocks to TFP. Estimation results for equation (5) based on provincial aggregates over the period 1991-2011 are reported in table 3. They provide tests of hypotheses (ii) and (iii), that the elasticity of the output:labor ratio with respect to the real wage exceeds 1.0, and its elasticity with respect to the stock of physical capital is positive. To correct for the likelihood of simultaneous equation bias in estimation of the wage coefficient with provincial aggregate data, we employ two-stage least squares (2SLS), where the instrumental variable (IV) for the provincial real wage is the 10-year lagged size of the provincial primary-industry labor force[7].

The point estimates of approximately 1.6 for the coefficients of the one-year lagged log wage are highly significant in column (1) of table 3, but the Stock-Yogo test statistics for weak identification is only moderately strong. Moreover, the p-value for the test that the estimated coefficient of log real wage is greater than 1.0 is 0.35. Thus, we cannot with a high degree of confidence reject the null hypothesis that the coefficient of log real wage equals 1.0, indicating the absence of wage-induced technical change. The estimated coefficient on the stock of physical is not significantly different from zero in column (1). These results provide no evidence that exogenous increases in the stock of physical capital or the wage induce laborsaving technological change.

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[6] Our key theoretical results shown in equations 5 and 7 are conditioned on capital stock *K*. However, the functional form of the conditioning is unknown. We use a simple log linear function of *K* in the main text, but we also conducted extensive robustness check using fractional polynomials and splines. Specifically, we estimated the following specifications:

$$\ln\left(\frac{Y}{L}\right)_{it} = \alpha_{it} + \beta_t \ln W_{it} + m\left(K_{it} \text{ or} \ln K_{it}\right) + \varepsilon_{it} \quad (5') \text{ and}$$

$$\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \alpha_t \ln\left(\frac{K}{L}\right)_{it} + \gamma_t \ln W_{it} {}^{*} \ln\left(\frac{K}{L}\right)_{it} + m\left(K_{it} \text{ or} \ln K_{it}\right) {}^{*} \ln\left(\frac{K}{L}\right)_{it} + \varepsilon_{it} \quad (7')$$

Where *m*(.) is either a fractional polynomial function or a spline function. This allows us to control for a wide variety of trends in *K*, which is not an essential part of our analysis. Estimates of primary parameters, i.e. α, β,and γ, are very close to those in the baseline specifications. Estimation results are also robust to inclusion of county-specific fixed effects. Detailed results are available upon request.

[7] Estimation results are robust to alternative specifications of the time period for the IV and when estimated over a longer time period for the basic equation.

In contrast to a broad literature[8] linking FDI and R&D to innovation, in the presence of the log-wage variable, we find no support for a positive link of R&D and/or foreign ownership participation to technology growth (see columns (3)-(6) of table 3).

Empirical Results for Hypotheses (ii)-(iii): Tests with LME data.

We report regressions based on three sets of the LME data based on firm size as defined in the survey instrument: (i) Large enterprises; (ii) Medium and Large enterprises; (iii) All enterprises. For clarity of presentation, estimation results are reported in panels A of figures 6-8[9]. The use of microdata allows us to account for the fact that innovation is more likely among Large firms as suggested in much of the literature on innovation in China (An, 2017). Focusing on the Large subsample may provide clearer evidence of price-induced laborsaving innovation compared to the provincial aggregates.

In estimating equation (5) using the LME samples, it seems reasonable to assume that local wage rates are not influenced by individual firm employment decisions, and we proceed on the assumption that enterprises' stock of physical capital are exogenous and predetermined as discussed above. We include county- and year-fixed effects, as well as regional trend variables as additional controls. These are similar to the controls included in our provincial models, but we now include county rather than province fixed effects. The extremely large LME sample sizes contribute to highly significant estimated regression coefficients and permits the estimation of individual year interactions with both the wage and capital stock variables. The estimated coefficients for the parameters β and δ (the wage and capital stock coefficients) are illustrated in figures 6a through 8a, respectively[10].

We see in figure 6 panel A that the estimated value of β for the two subsamples that exclude the smaller firms generally exceeds 1.0 through the period 1996-2001, but declines abruptly and remains well below 1.0 between 2001 and 2003, not rising above 1.0 through 2007. Thus the null of no wage-induced technical change is strongly rejected for these two subsamples over the period 1996-2001.

[8] Much of this literature is summarized in An, 2017.
[9] Estimation results in tabular form with statistical significance of coefficients are available on request.
[10] We believe that assuming physical capital K is exogenous and predetermined is reasonable, given the very imperfect financial markets in China (Ge and Yang, 2014 provide a similar argument for assuming exogeneity and show that estimation results are robust when an IV procedure is used.)

The estimated value of β for the full sample, including the smaller-size firms in the LME data, is consistently less than 1.0 from 1998 through 2007, and its time path follows a roughly similar course to that of the larger-firm subsamples, falling steadily through 2003, rebounding somewhat, but ending in 2007 significantly below its value in 1998.

Our primary focus is to identify whether enterprises in China have responded to rising labor costs with labor-saving innovation, either through domestic innovative activity or indirectly through adapting labor-saving technology already available at the world technology frontier. The inclusion of a measure of physical capital in equation (5) serves not only to identify the impact of exogenous shocks to capital-availability on domestic innovation, but more importantly, to control for omitted variable bias in estimates of the impact of wage increases on technical change. In panel A of figure 7, we show that the estimates of the coefficient β estimated excluding the capital-stock variable is very robust to exclusion of the capital-stock variable.

The estimated coefficients of physical capital δ, shown in figure 8, are consistently positive for the two larger-firm LME samples, and above zero after the year 2000 in the sample including all firms. Their time paths tend to reflect in reverse the paths of coefficients for log real wage, abruptly increasing between 2001 and 2003, while β falls. We conjecture that after China's accession to WTO increased international competition forced lower-productivity firms to become more competitive if they were to survive in the international marketplace, and this struggle made access to loanable funds even more critical for a firm's than it had been.

Modeling θ:

An alternative implementation of the induced innovation framework can aid in testing the robustness of our estimation results. Thus we approach the relationship between labor productivity and the price of labor is developed by taking logs of (3) and adding location and date identifiers, to obtain

$$\begin{aligned} &\ln\left(\frac{Y}{L}\right)_{it} = \mathrm{B}_{it} + \theta \ln\left(\frac{\bar{K}}{L}\right)_{it} \quad \text{where} \\ &\mathrm{B}_{it} = \frac{1}{\alpha}\ln A_{it} - \ln \alpha(1-\alpha) \end{aligned} \qquad \textbf{(6)}$$

for $t = 0 \ldots \mathrm{T}$.

We want to know whether the technology parameter θ is a function of the real wage. To test this hypothesis we need to hold constant the influence of the availability of physical capital, and we specify:

$$\theta = \gamma_0 + \gamma_1 f(W) + \gamma_2 f(\bar{K}),$$
$$\text{where } f(X) = \ln X$$

Under wage-induced technical change, we expect $\gamma_1 > 0$. Substituting the preceding specification into (6) we obtain the empirical formulation[11]:

$$\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \gamma_0 \ln\left(\frac{\bar{K}}{L}\right)_{it} + \gamma_1 f(W_{it}) \ln\left(\frac{\bar{K}}{L}\right)_{it} + \gamma_2 f(K_{it}) \ln\left(\frac{\bar{K}}{L}\right)_{it} + \varepsilon_{it} \qquad \textbf{(7)}$$

Based on this specification, we formulate:

***Hypothesis iv*: $\gamma_1 > 0$**

***Hypothesis v*: $\gamma_2 > 0$**

<u>Hypotheses (iv) and (v): Tests with Provincial data.</u>

Estimation results for equation (7) based on provincial aggregates over the period 1991-2011 are reported in table 4. As in estimation of equation (5) using the provincial aggregate data, we use 2SLS, where the IV for the provincial real wage is the 10-year lagged size of the provincial primary-industry labor force.

The estimate of γ_1 is significantly greater than zero in column (1), while that of γ_2 is significantly less than zero. Our estimate of γ_1 supports the hypothesis of wage-induced technical change, though the estimate of γ_2 does not support the hypothesis that increases in capital stock induced innovation.

<u>Hypotheses (iv) and (v): Tests with LME data.</u>

We believe that the innovation gap between small and large firms is likely to obscure aspects of endogenous innovation in estimates based on the provincial aggregates. If so, estimating equation (7) using LME data would be more revealing. The results are presented in panels B of figures 6-8. Estimation results for γ_1 are robust to the exclusion of the $f(K_{it}) \ln\left(\frac{\bar{K}}{L}\right)_{it}$ regressor, similar to the exclusion of the variable *K* in estimation of equation (5).

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[11] As noted above our estimation results are robust to a variety of alternative specifications.

After 1998, the time paths of γ_1 are closely parallel for all subsamples of the LME data, dropping substantially through 2003 (somewhat more so for the Large firm group) until leveling off through 2007 at about three-fourths their value in 1998. Moreover, the time paths for γ_1 are roughly similar to those for equation 5's β shown in figure 6a, particularly for the Large and Medium and Large firm subsamples. The estimated time paths of the wage coefficients based on both equations (5) and (7) indicate a substantial fall-off in the degree of wage innovation over time with the decline beginning in 2001 in the equation (5) results and earlier, in 1998, in the equation (7) results.

The estimated values of γ_2 reported in panel B of figure 8 contrast with the estimated values of δ in panel A. The estimated values of γ_2 are positive only for the large-firm LME subset, and only for the years 1996-1998 and 2007. For the larger sample of medium plus the largest firms, there is a similar trajectory, with the estimated γ_2 being zero or less through the entire sample period. The estimated values of γ_2 for the sample of all LME firms is always negative and lies well below those for the other two samples, only weakly reflecting an upward trend beginning in 2003. This trajectory is similar to that reported for δ in panel B, although our estimated γ_2 begins to rise in 2003 rather than 2001.[12] The upward trend of the paths of δ and γ_2 for the two subsamples containing the larger LME firms suggest that access to funds for financing investment in physical capital had greater impacts on innovation after China's accession to WTO as competitive pressures increased and access to investible funds became more critical for firms' survival.

We conjecture that the mixed evidence regarding the impact of exogenous shocks to physical capital on capital-using (labor-saving) innovation is due in part to the better access of SOE's to loanable funds (Song, et al., 2011) while they appear to be less effective than privately-owned enterprises in spending on R&D (Wei, Xie, and Zhang, 2017).

4. Comparison with Other Evidence on Innovation.

We find the absence of wage-induced innovation following WTO surprising on its face, and also in light of evidence that factor-neutral productivity (TFP) growth was boosted by WTO

[12] Absence of data for 2002 and 2004 in the Large and Large + Medium firm LME samples makes timing of this break point difficult.

accession (Brandt, et al, 2012; Brandt, et al, 2017). However, An (2017) notes that "Compared with 2002, the percentage of first world innovation in product and process declined sharply [in 2014]…indicating that the level of 'Created in China' was literally dropping."

TFP Growth. We explore the path of TFP growth in figure 9, where in panel A, we compare the growth in TFP from Wei, Xie, & Zhang (2017) to the growth in TFP calculated from the All-Firms sample of the LME data. We find that that calculated TFP growth fell sharply in the two full years after China's WTO accession (2003 and 2004) before rebounding as reflected in both series in panel A.

In panel B we explore the degree to which the unexplained portion of productivity growth represented by TFP is reduced by inclusion of arguments representing wage-induced innovation. The time path of TFP growth derived from equation (6) with the large-firm subsample exhibits wide variation over time, while the TFP growth series net of the variables representing induced innovation held constant in equation (7) is almost flat, indicating a substantial contribution of induced innovation to TFP growth. In sharp contrast to the TFP growth series based on the Large-Firm subsample, the comparably paired series estimated with All LME firms lie almost on top of each other, consistent with production elasticities varying minimally over time and indicating little if any contribution of wage-induced innovation to the growth of labor productivity in the LME sample that is dominated by the smallest firms..

This is not to say that entering WTO had small or even negative productivity impacts, but that its contribution to GDP- and labor-productivity growth appears to have been attributable to weeding out non-competitive enterprises and causing a reallocation of resources toward more efficient entrepreneurs in the private sector (as shown, e.g., by Hsieh & Klenow, 2009 and Song, et al., 2011). Fan, et al. (2017) demonstrates that firms with low productivity pre-WTO that did not exit post-WTO generally survived by upgrading quality of output and becoming more competitive in high-income export markets.

R&D and Patent Activity. Direct evidence on whether China is innovating in response to rising labor costs (in addition to simply substituting against labor under given technology) can be compared with indirect evidence of innovation reflected in research and development (R&D) and patent activity. China's "patent explosion" has been explored and documented in great detail by Hu and Jefferson (2009) and is covered thoroughly by Wei, Xie, and Zhang (2017). In figures 10 and 11 we plot the time paths of the annual growth of China's R&D stock (our calculations) and the proportion of China's invention patents in total patent applications and total patents granted (Wei, Xie, & Zhang, 2017 Appendix), respectively. The R&D series surges between 1998 and 2000 and in the patent series between 1999 and 2004. As illustrated in figure 11, the proportion of invention patents in total patent applications for grew from 25% to over 35% between 1995 and 2004, and the percentage of invention patents in the total granted grew much more sharply. However, the paths of both proportions level off after 2004, and decline slightly through 2011 (for applications) and through 2014 (for grants). The leveling off of the two patent series after 2003 is broadly consistent with the decline in the series tracking wage-induced innovation from equations (5) and (7). Perhaps the productivity gains falling to the benefit of relatively efficient firms after WTO entry temporarily offset the pressures of rising wage rates, thus softening their impact on profits and the need to innovate, but the response of innovation to China's WTO access is clearly a topic meriting additional research.

In our framework, innovation is embodied in physical capital. As Nelson (1964) and Wolff (1991) have shown, a measure of the time-path of the degree that new technology embodied in physical capital is the acceleration of the physical capital stock. Figure 12 presents a 3-year centered moving average of the acceleration of China's secondary-industry physical capital stock derived from the provincial data along with the log-wage and log-K (large firms) coefficients from equation (7). The time path of physical-capital acceleration suggests a decline in the growth of capital-embodied technology through and the year 2002 followed by a modest recovery. The dip in the acceleration series approximately tracks the decline of the log-wage coefficient through 2003, and its increase matches the leveling-off of the log-wage coefficient series and upward drift of the log-K series from 2003 through 2007.

5. **Summary and Conclusion.**

We implement a model developed in Acemoglu (2010) and Acemoglu and Autor (2011) to investigate evidence bearing on induced innovation in China in response to increasing labor costs. Under induced innovation, when an input becomes increasingly scarce (e.g., labor), new technology is factor-saving. Based on an assumed unitary elasticity of substitution, the model provides testable hypotheses relating the rate of labor productivity growth to real wage growth and the availability of physical capital. That is, labor productivity growth will equal wage growth as capital is substituted for labor under fixed technology and will exceed wage growth if there is wage-induced innovation. Our empirical results, based on firms in secondary industry, provide evidence to support wage-induced innovation. We find that induced innovation was concentrated among the largest firms, occurring in China during the period beginning in the mid-1990s and tapering off significantly after China's entry into WTO. We conjecture that constraints on access to funds for financing investment in physical capital had greater impacts on innovation after China's accession to WTO. Increased international competition forced lower-productivity

Our conclusions are somewhat sensitive to the assumed elasticity of substitution between capital and labor. If the elasticity of substitution exceeds unity, then labor productivity growth will exceed wage growth even under fixed technology. This could lead us to falsely reject the null of fixed technology in the results presented in section three. If the elasticity of substitution is below unity, then labor productivity growth should be less than wage growth under fixed technology. This would imply our hypothesis tests are biased against rejecting the null when it is false. Bai and Qian (2010) report an elasticity of substitution equal to 1, and Mallick (2012) finds that that the elasticity of substitution between capital and labor in China is significantly less than unity. Thus we believe that our hypothesis tests are biased against finding evidence of induced technical change, which strengthens our results.

The evidence of substantially reduced wage-induced innovation in the approximately five years following China's accession to WTO is quite robust to estimation with different subsamples of our data and to specifications of regression models. Again, our inferences could be biased if our assumption of unitary elasticity of substitution is false. If the elasticity of substitution between capital and labor is equal to or less than unity, a decline in the rate of labor productivity growth below the rate of wage growth could still be consistent with induced innovation. It could also be that the elasticity of substitution fell (further) below unity during this same period. Although we find this assumption to be implausible, further work is needed to pin down estimates of the elasticity of substitution between capital and labor, to better understand the evolution of production technology in response to rising labor costs in China.

Technical Appendix

Purpose: use Acemoglu's model to construct an example to show how the wage-induced technology change affects the share parameters in the production function.

Assumptions:

- A representative firm produces the final good using two factors of production, labor and capital. The price of the final good is normalized to one.
- Technologies are created and supplied by a profit-maximizing monopolist.
- In Acemoglu's M economy (Section C, p.1046), the supplies of the productive factors are assumed to be given. In our setup, we assume the supply of *K* and the wage *W* are given: the goal is to show how wage affects the advancement of wage-induced technologies. The supply of *K* is fixed at $\bar{K}$.

Final-Good Producer

The objective function of the final-good producer:

$$\max_{K,L,q(\theta)} \alpha^{-\alpha}(1-\alpha)^{-1}\left(K^{\theta}L^{1-\theta}\right)^{\alpha} q(\theta)^{1-\alpha} - W \cdot L - R \cdot K - \chi q(\theta)$$

θ: technology

$q(\theta)$: quantity of an intermediate good embodying technology θ

χ: price of the intermediate good

$\alpha^{-\alpha}(1-\alpha)^{-1}$: a convenient normalization used in Acemoglu (2010); $\alpha \in (0,1)$.

FOCs:

$[L]$: $W = \alpha^{1-\alpha}(1-\alpha)^{-1}(1-\theta)\left(K^{\theta}L^{1-\theta}\right)^{\alpha-1}K^{\theta}L^{-\theta}q(\theta)^{1-\alpha}$

$[K]$: $R = \alpha^{1-\alpha}(1-\alpha)^{-1}\theta\left(K^{\theta}L^{1-\theta}\right)^{\alpha-1}K^{\theta-1}L^{1-\theta}q(\theta)^{1-\alpha}$

$[q(\theta)]$: $\alpha^{-\alpha}(1-\alpha)^{-1}(1-\alpha)\left(K^{\theta}L^{1-\theta}\right)^{\alpha}q(\theta)^{-\alpha} = \chi$

⇨ $q(\theta) = \alpha^{-1}\chi^{-1/\alpha}\left(K^{\theta}L^{1-\theta}\right)$

$$\begin{aligned} W &= \alpha^{1-\alpha}(1-\alpha)^{-1}(1-\theta)\left(K^{\theta}L^{1-\theta}\right)^{\alpha-1}K^{\theta}L^{-\theta}q(\theta)^{1-\alpha} \\ &= \alpha^{1-\alpha}(1-\alpha)^{-1}(1-\theta)\left(K^{\theta}L^{1-\theta}\right)^{\alpha-1}K^{\theta}L^{-\theta}\left[\alpha^{-1}\chi^{-1/\alpha}\left(K^{\theta}L^{1-\theta}\right)\right]^{1-\alpha} \end{aligned}$$

$= (1-\alpha)^{-1}(1-\theta)K^{\theta}L^{-\theta}\chi^{(\alpha-1)/\alpha}$

$\Rightarrow \; L = K\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{\frac{1}{\theta}}\chi^{\frac{\alpha-1}{\alpha\theta}}$

At the equilibrium, $K = \bar{K}$. Then $L = \bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{\frac{1}{\theta}}\chi^{\frac{\alpha-1}{\alpha\theta}}$, and $q(\theta) = \alpha^{-1}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{\frac{1-\theta}{\theta}}\chi^{\frac{\alpha-1-\alpha\theta}{\alpha\theta}}$.

The Profit-Maximizing Monopolist

Assumptions:

(1) A technology θ is created at a cost $C(\theta)$.

$\theta = \frac{1}{1+e^{\phi}} \;\Rightarrow\; \phi = \ln(\frac{1}{\theta} - 1)$

Assume $C(\theta) = \left[\ln\left(\frac{1}{\theta} - 1\right)\right]^2$.

(2) Once the technology θ is created, the unit production cost is assumed to be $\frac{1-\alpha}{1-\alpha+\alpha\theta}$ units of the final good. Since the price of the final good is normalized to 1, the unit production cost of the intermediate good is $\frac{1-\alpha}{1-\alpha+\alpha\theta}$.

$$\max_{\chi,\theta}\left(\chi - \frac{1-\alpha}{1-\alpha+\alpha\theta}\right)\cdot\alpha^{-1}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{\frac{1-\theta}{\theta}}\chi^{\frac{\alpha-1-\alpha\theta}{\alpha\theta}} - C(\theta)$$

$[\chi]$: $\chi^{\frac{\alpha-1-\alpha\theta}{\alpha\theta}} + \left(\chi - \frac{1-\alpha}{1-\alpha+\alpha\theta}\right)\frac{\alpha-1-\alpha\theta}{\alpha\theta}\chi^{\frac{\alpha-1-\alpha\theta}{\alpha\theta}-1} = 0$

$\Rightarrow \; \chi = 1$

Given $\chi = 1$, The problem of the monopolist can be simplified as follows:

$$\max_{\theta}\frac{\theta}{1-\alpha+\alpha\theta}\cdot\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{\frac{1-\theta}{\theta}} - \left[\ln\left(\frac{1}{\theta} - 1\right)\right]^2$$

FOC: $\frac{1}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{(1-\theta)/\theta}\left(\frac{\alpha\theta}{1-\alpha+\alpha\theta} + \frac{1}{\theta}\ln\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)\right) = 2\ln(\frac{1}{\theta} - 1)\frac{1}{\theta-\theta^2}$ (1)

For the existence of θ^*, we require $(1-\alpha)W$ to be greater than 1:

$\lim_{\theta\to 0}\frac{\theta}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{(1-\theta)/\theta} = 0 < \lim_{\theta\to 0}\left[\ln\left(\frac{1}{\theta} - 1\right)\right]^2$

$\lim_{\theta\to 1}\frac{\theta}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{(1-\theta)/\theta} = \frac{\bar{K}}{1-\alpha} < \lim_{\theta\to 1}\left[\ln\left(\frac{1}{\theta} - 1\right)\right]^2$

It is easy to show that the LHS of (1) is negative given $(1-\alpha)W > 1$ and its RHS is negative only when $\theta > 0.5$, so θ^* must be between 0.5 and 1.

The objective function of the monopolist has strictly increasing differences in (W, θ) if and only if $\frac{\partial^2 \frac{\theta}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{(1-\theta)/\theta}}{\partial W \partial \theta} > 0$.

$$\frac{\partial^2 \frac{\theta}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{(1-\theta)/\theta}}{\partial W \partial \theta} = \frac{1}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{W}\right)^{1/\theta}\left(\frac{1}{1-\alpha}\right)^{(1-\theta)/\theta}\frac{1}{\theta^2}\left[\begin{array}{c}\frac{\alpha\theta^2}{1-\alpha+\alpha\theta} + \ln\left(\frac{1}{1-\alpha}\right) + \\ \ln\left(\frac{1-\theta}{W}\right) + \frac{\theta}{1-\theta}\end{array}\right]$$

$\frac{\partial^2 \frac{\theta}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{\frac{1-\theta}{\theta}}}{\partial W \partial \theta} > 0$ requires that $W < \frac{1-\theta}{1-\alpha}e^{\frac{\alpha\theta^2}{1-\alpha+\alpha\theta}+\frac{\theta}{1-\theta}}$. It is easy to show that $\frac{1-\theta}{1-\alpha}e^{\frac{\alpha\theta^2}{1-\alpha+\alpha\theta}+\frac{\theta}{1-\theta}}$ is strictly increasing in θ. Then, we define W_{max} as $\frac{1-0.5}{1-\alpha}e^{\frac{\alpha\times0.5^2}{1-\alpha+\alpha\times0.5}+\frac{0.5}{1-0.5}}$, which should be larger than $\frac{1}{1-\alpha}$. Please note that $W < W_{max}$ is only a sufficient condition to ensure the objective function of the monopolist has strictly increasing differences in (W, θ).

Given that (a) the objective function is continuously differentiable in θ, (b) $\frac{1}{1-\alpha} < W < W_{max}$ (which ensures that the existence of the solution and the objective function of the monopolist has strictly increasing differences in (W, θ)), and (c) the solution is strictly between 0.5 and 1, Topkis's theorem implies that $\frac{\partial\theta^*}{\partial W} > 0$. In other words, an increase in W can encourage technological advancement, which we define as a wage-induced technical change.

$$\frac{\partial^2 \frac{\theta}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{(1-\theta)/\theta}}{\partial \bar{K}\partial\theta} = \frac{1}{1-\alpha+\alpha\theta}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{(1-\theta)/\theta}\left[\frac{1-\alpha}{1-\alpha+\alpha\theta} + \frac{1}{\theta}\ln\left(\frac{W(1-\alpha)}{1-\theta}\right) - 1\right]$$

Given $\frac{1}{1-\alpha} < W < W_{max}$, it is easy to show that $\frac{1-\alpha}{1-\alpha+\alpha\theta} + \frac{1}{\theta}\ln\left(\frac{W(1-\alpha)}{1-\theta}\right) - 1 > 0$. In other words, the objective function of the monopolist has strictly increasing differences in $(\bar{K}, \theta)$. Then, by the same token, Topkis's theorem implies that $\frac{\partial\theta^*}{\partial\bar{K}} > 0$. In this regime, an increase in capital will also encourage technological advancement, which we define as a capital-induced technical change.

Output Per Worker

$$\frac{\alpha^{-\alpha}(1-\alpha)^{-1}\left(\bar{K}^\theta L^{1-\theta}\right)^\alpha q(\theta)^{1-\alpha}}{L} = \frac{\alpha^{-\alpha}(1-\alpha)^{-1}\left(\bar{K}^\theta L^{1-\theta}\right)^\alpha\left(\alpha^{-1}\left(\bar{K}^\theta L^{1-\theta}\right)\right)^{1-\alpha}}{L}$$

$$= \frac{\alpha^{-1}(1-\alpha)^{-1}\overline{K}^{\theta}L^{1-\theta}}{L}$$
$$= \alpha^{-1}(1-\alpha)^{-1}\overline{K}^{\theta}L^{-\theta}$$
$$= \alpha^{-1}(1-\alpha)^{-1}\frac{W(1-\alpha)}{1-\theta}$$
$$= \frac{W}{\alpha(1-\theta)}$$

If θ is fixed, output per worker increases with W. An wage-induced technical change ($W \uparrow \Rightarrow \theta \uparrow$) will further increase the output per worker.

In addition, an increase in $\overline{K}$ will not affect the output per worker under fixed technology. In the presence of a capital-induced technical change, an increase in $\overline{K}$ will increase the output per worker.

Summary of the Model

The policy variables are $\overline{K}$ and W.

(i) Given $\overline{K}$, θ^* increases with W: an increase in W will encourage technological advancement, which we define as a wage-induced technical change.

(ii) Given W, θ^* increases with $\overline{K}$: an increase in $\overline{K}$ will encourage technological advancement, which we define as a capital-induced technical change.

(iii) Under fixed technology, the output per worker will increase with W (holding $\overline{K}$ fixed).

(iv) Wage-induced technical change will increase output per worker more than what would be expected on the basis of a pure substitution of capital for labor under fixed technology.

(v) An increase in $\overline{K}$ will not affect the output per worker under fixed technology (holding W fixed). If there is a wage-induced technical change, an increase in $\overline{K}$ will increase the output per worker.

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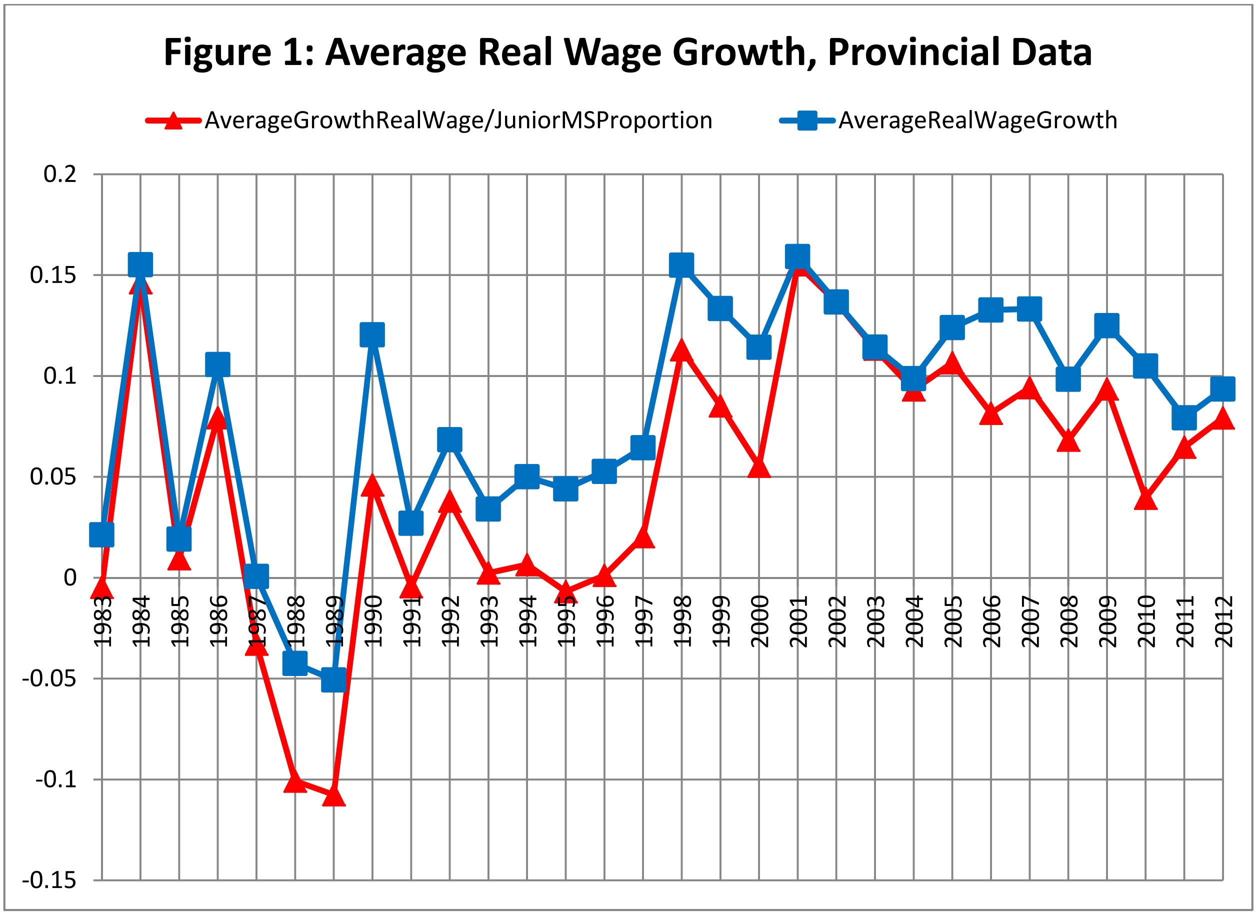
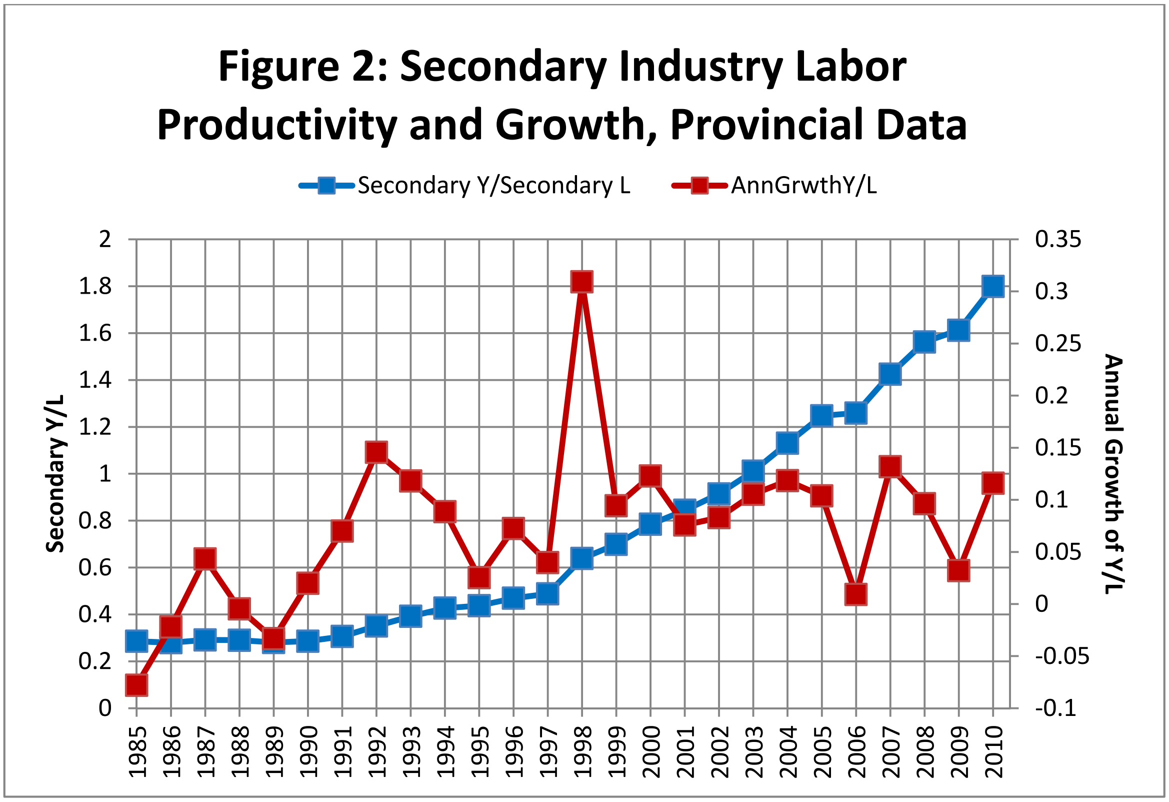
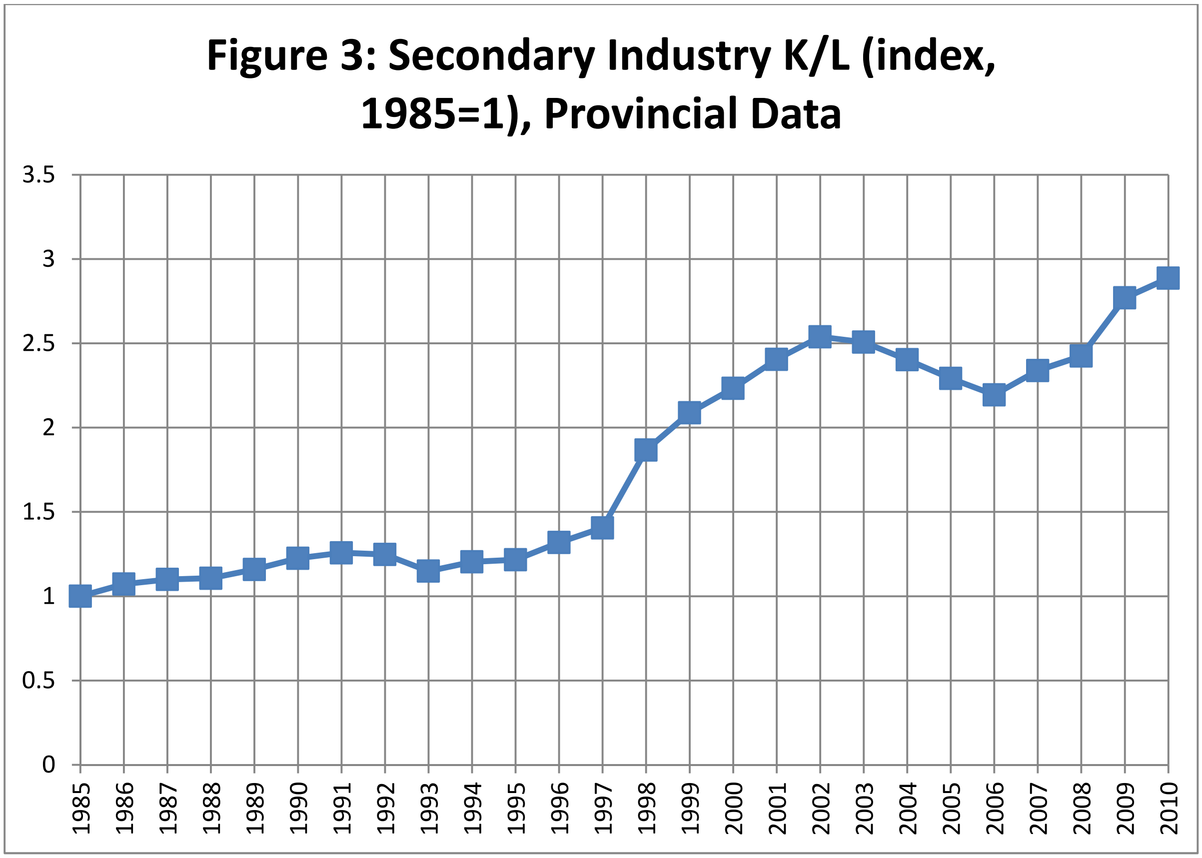


Source: Authors' calculations from China Statistical Yearbooks

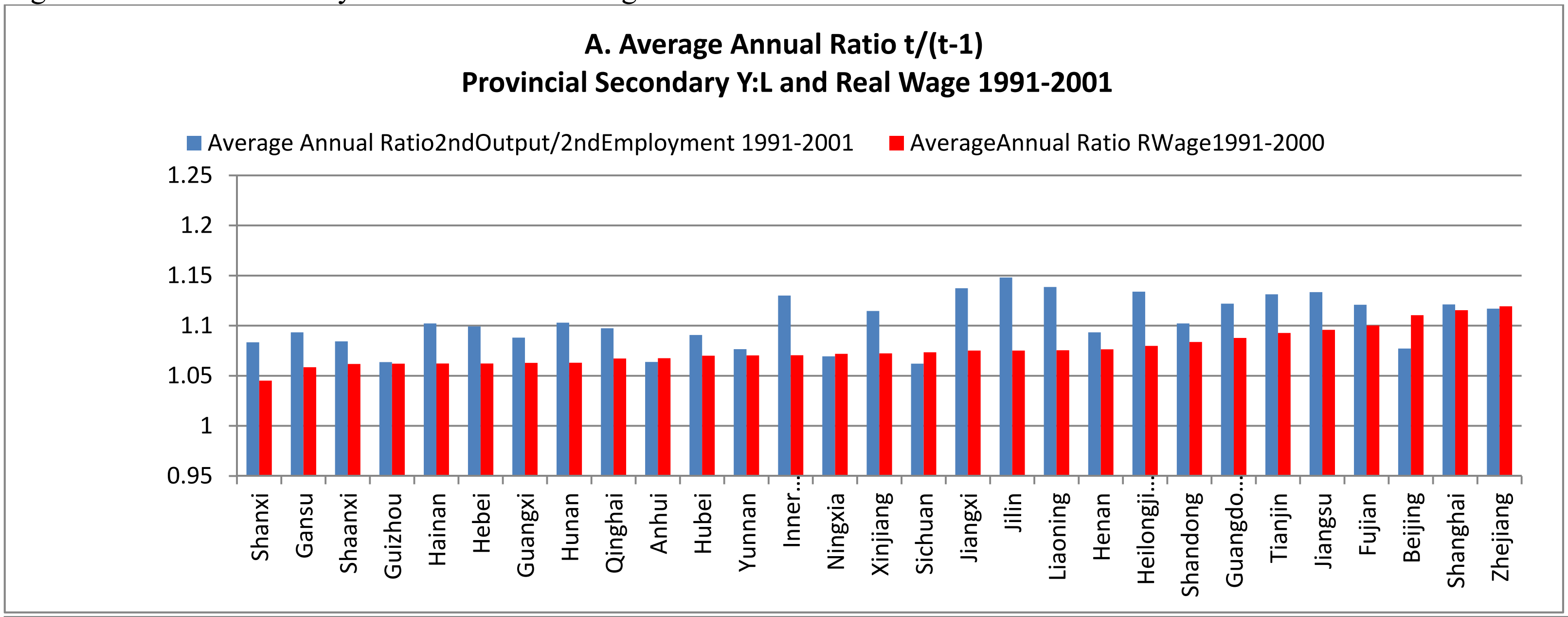


Source: Authors' calculations from China Statistical Yearbooks



Source: Authors' calculations from China Statistical Yearbooks

Figure 4 Labor Productivity Growth and Real Wage Growth



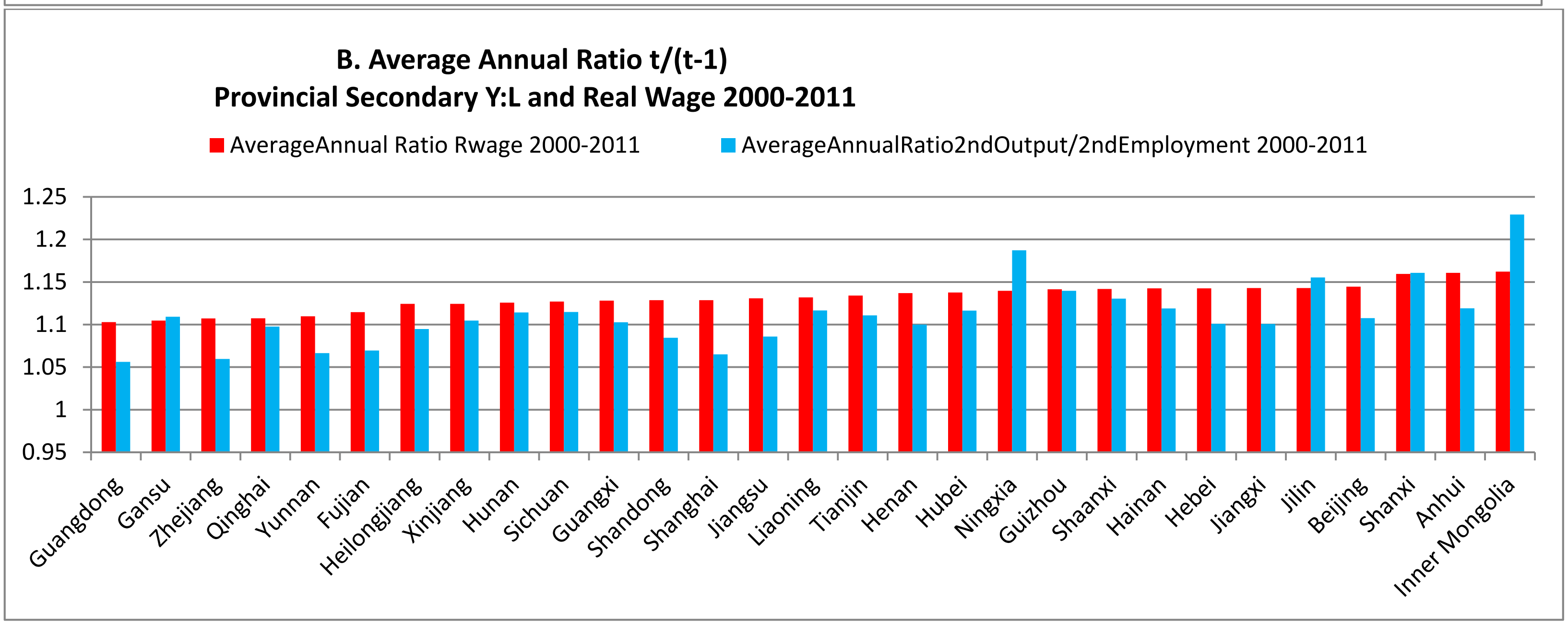
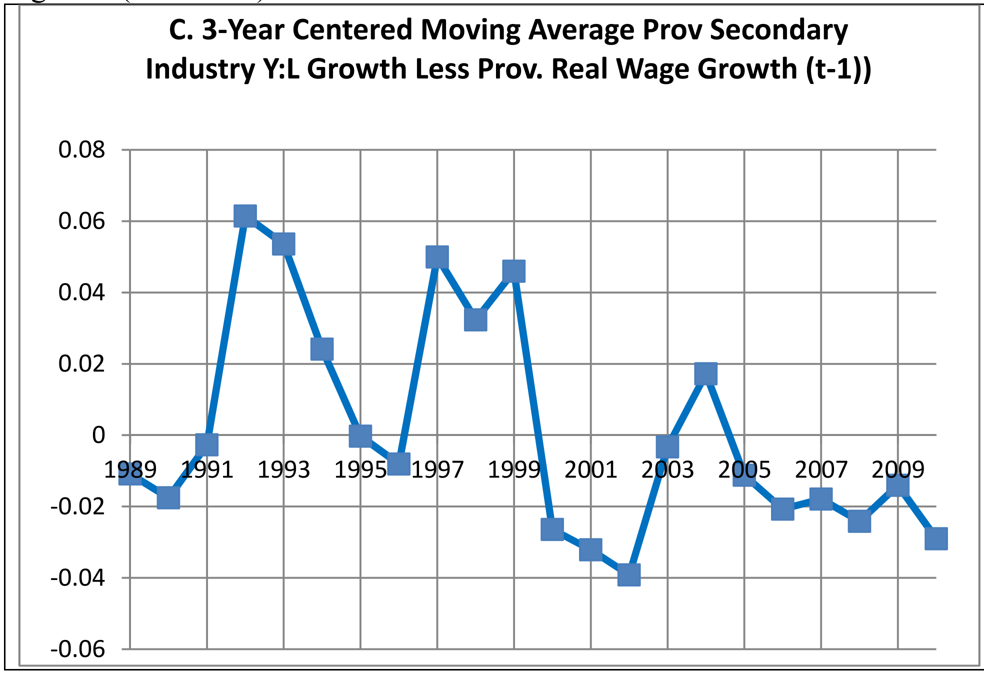
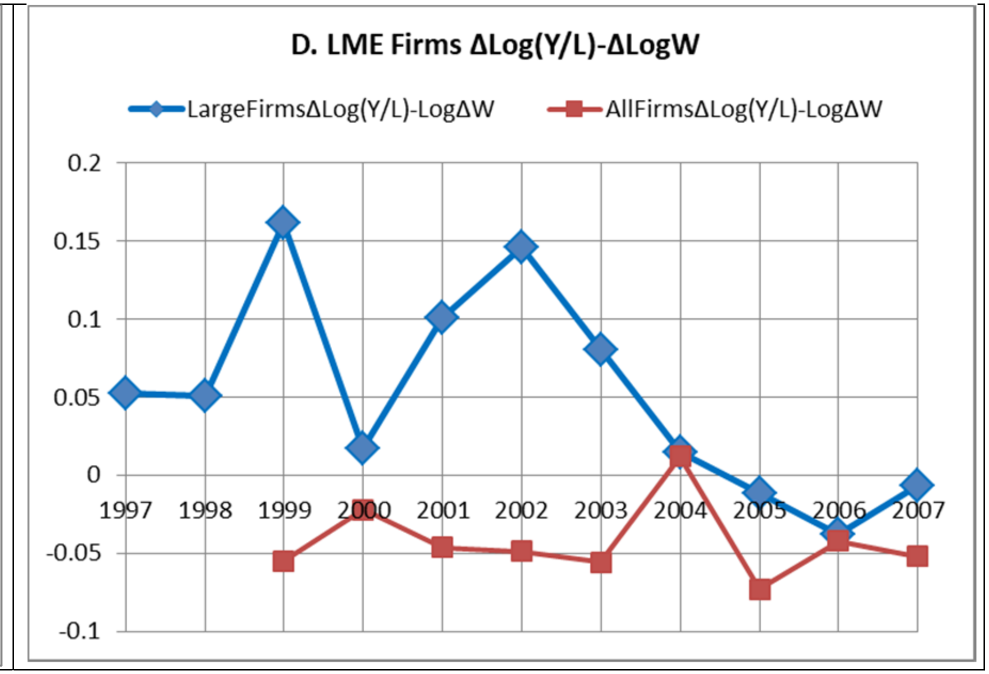


Figure 4 (continued)





Source: Authors' calculations from China Statistical Yearbooks and LME Surveys (full sample). Years 2002 and 2004 for Large Entperises are interpolated.

Figure 5 Estimates of Equation (4a) $(1-\theta_t)/(1-\theta_0)$.

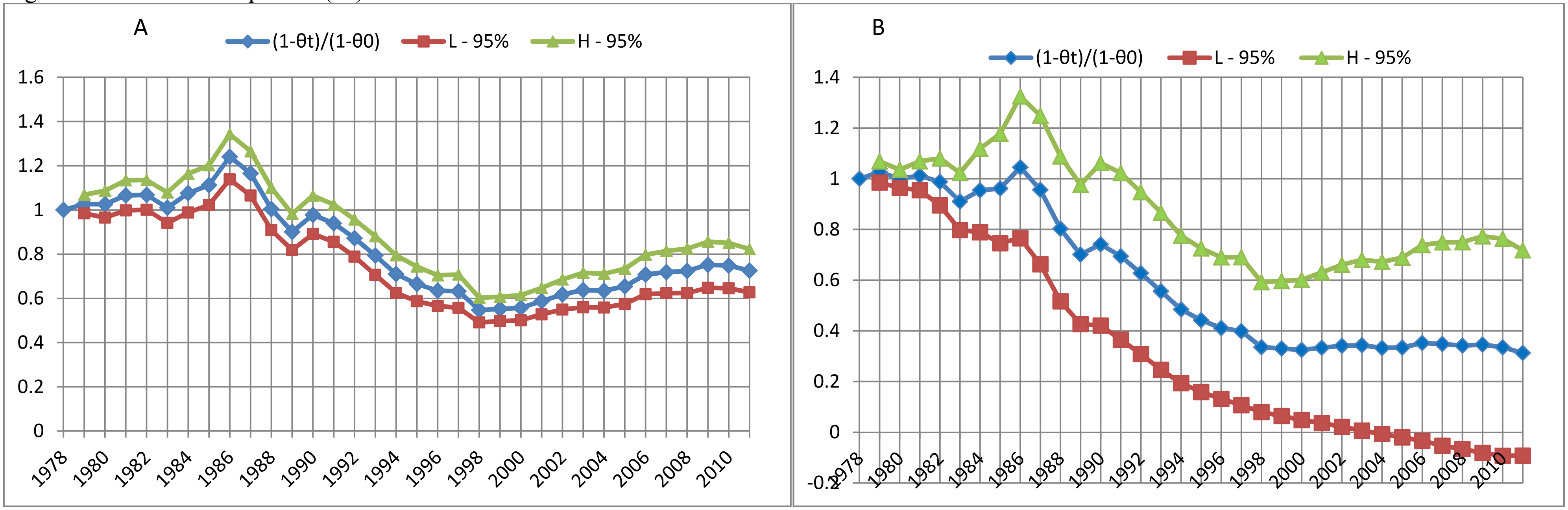
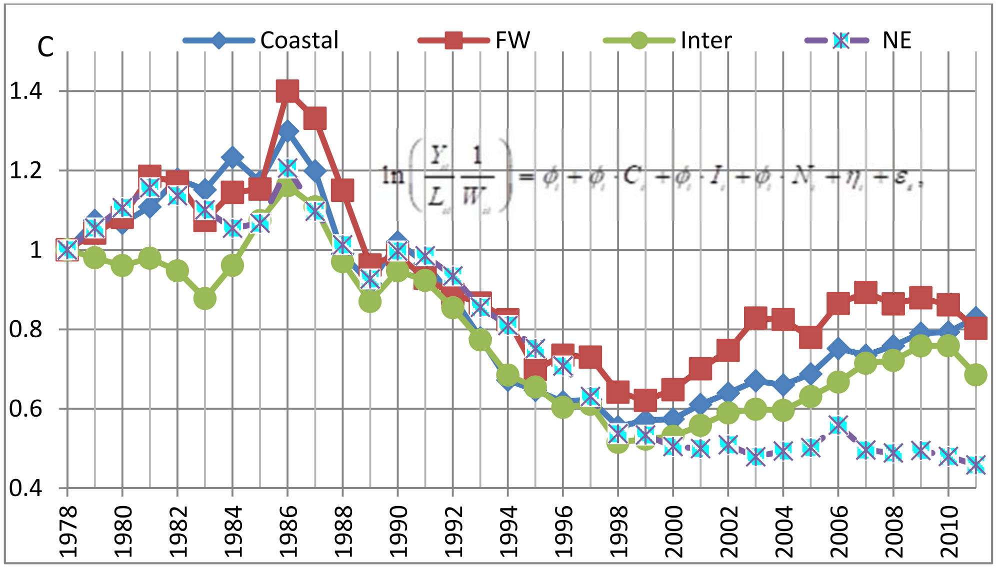
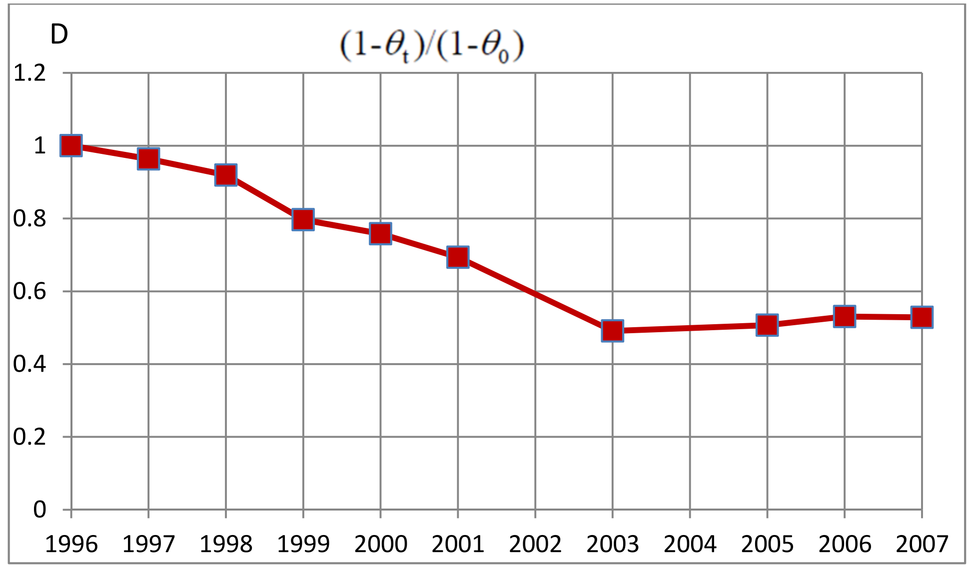


Figure 5 (cont.) Estimates of Equation (4a) $(1\text{-}\theta_t)/(1\text{-}\theta_0)$.



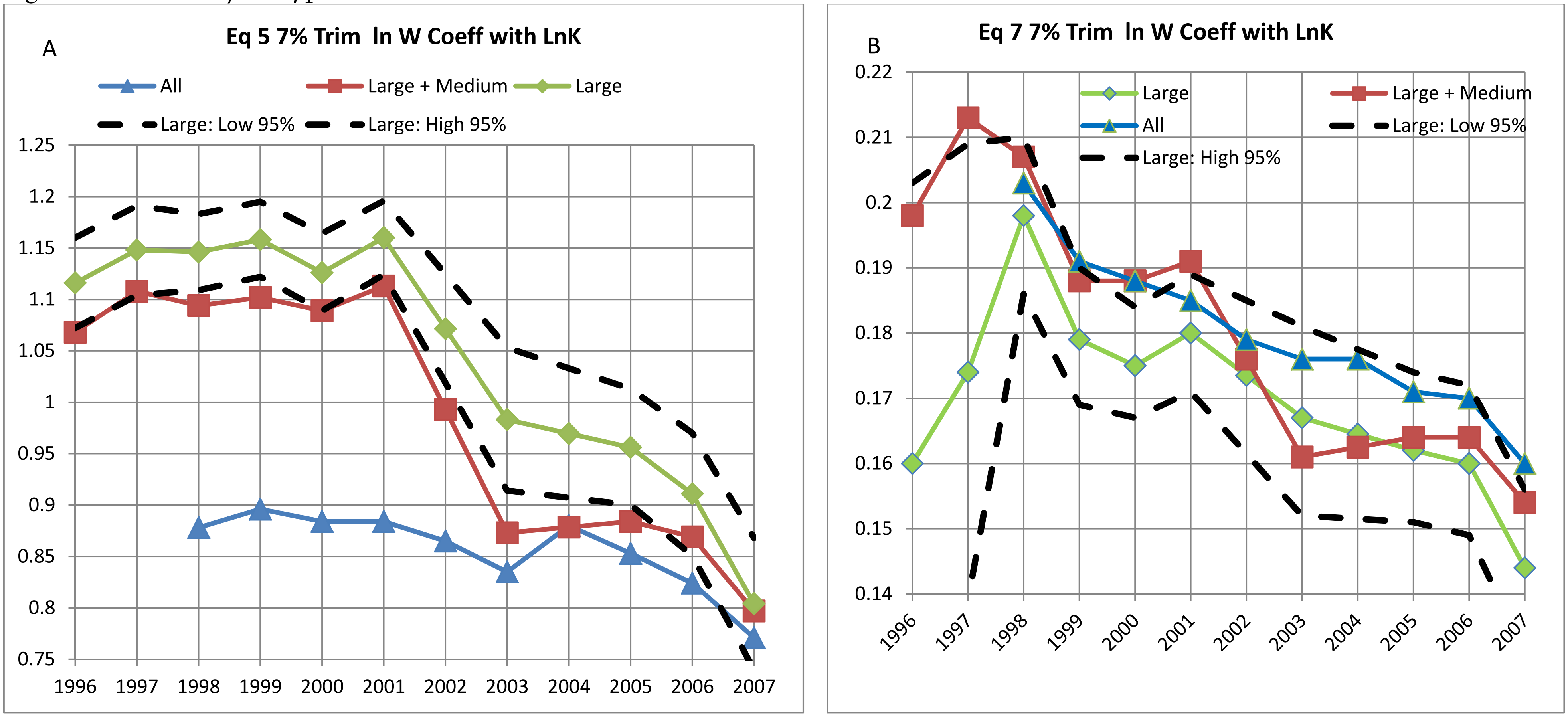


Source: Authors' calculations. Regions are Coastal (Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan);Interior (Shanxi, inner Mongolia, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Xichuan, Chongqing, Guizhou, Yunnan, and Shaanxi); Northeast (Liaoning, Jilin, and Heilongjiang); and Far West (Gansu, Qinghai,Ningxia, and Xinjiang).

(i) The estimates of Figure 6(c) are computed using the following regression shown in the chart where C, I, N are Coastal, Interior, and NE regions, respectively.

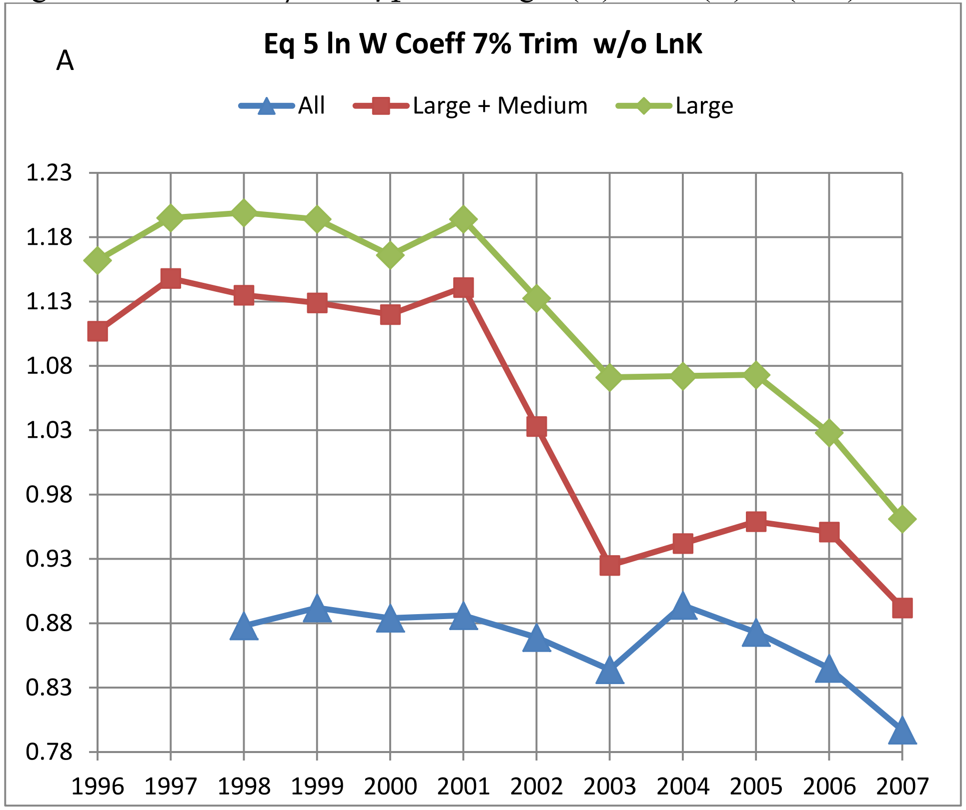
(ii) A-C Provincial Data; D LME Data Large Enterprises (7% Trim Sample)

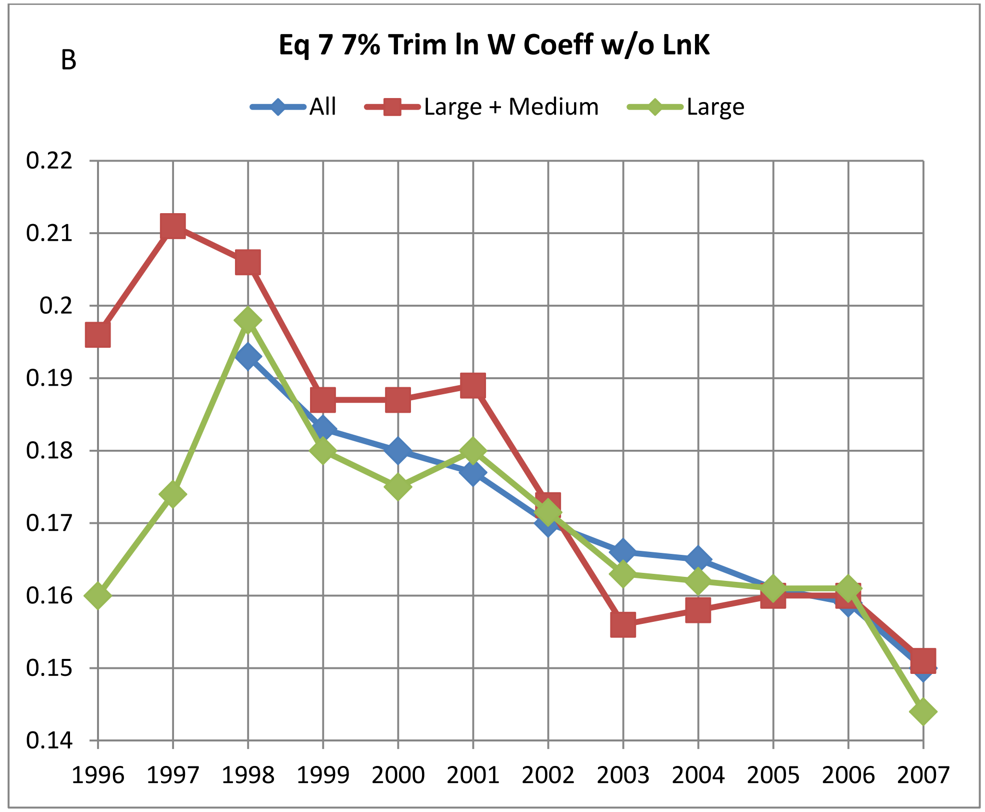
Figure 6 Estimates of β and γ_1



Source: Authors' calculations from LME data. Years 2002 and 2004 for Large and Large + Medium samples are interpolated

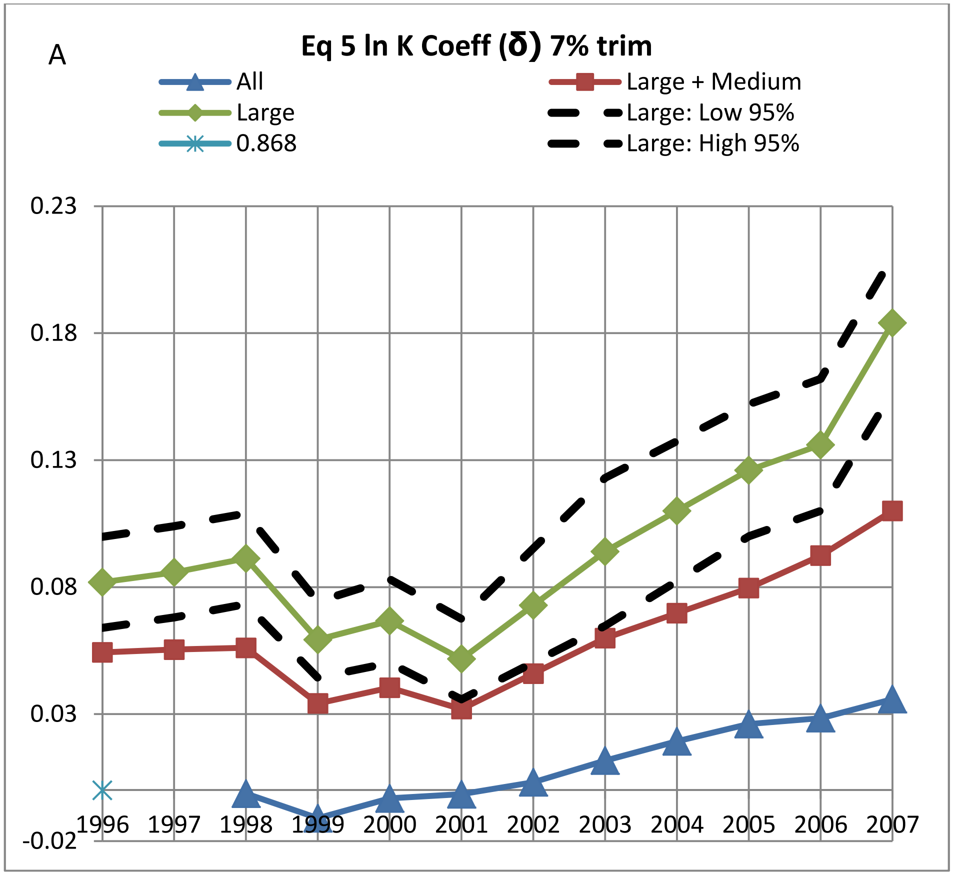
Figure 7 Estimates of β and γ_1 excluding ln(K) and ln(K)*ln(K/L)

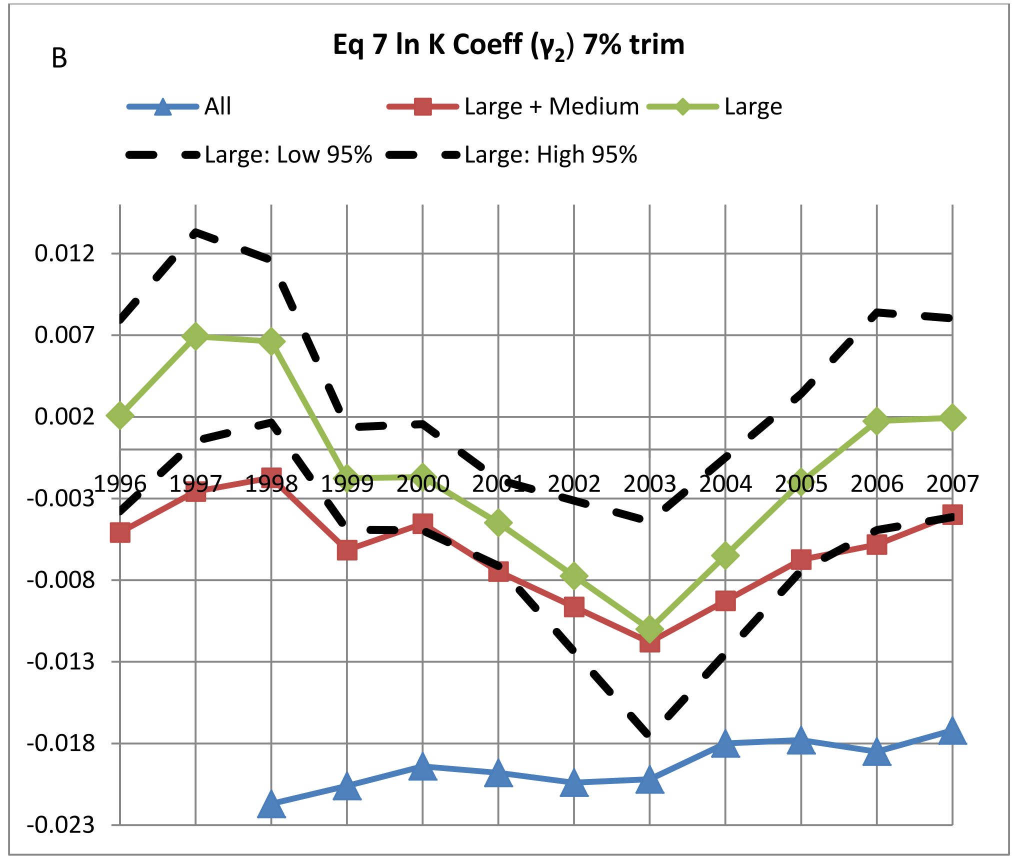




Source: Authors' calculations from LME data. Years 2002 and 2004 for Large and Large + Medium samples are interpolated

Figure 8 Estimates of δ and γ_2, LME Trimmed Samples





Notes: Authors' calculations from LME data. Years 2002 and 2004 for Large and Large + Medium samples are interpolated

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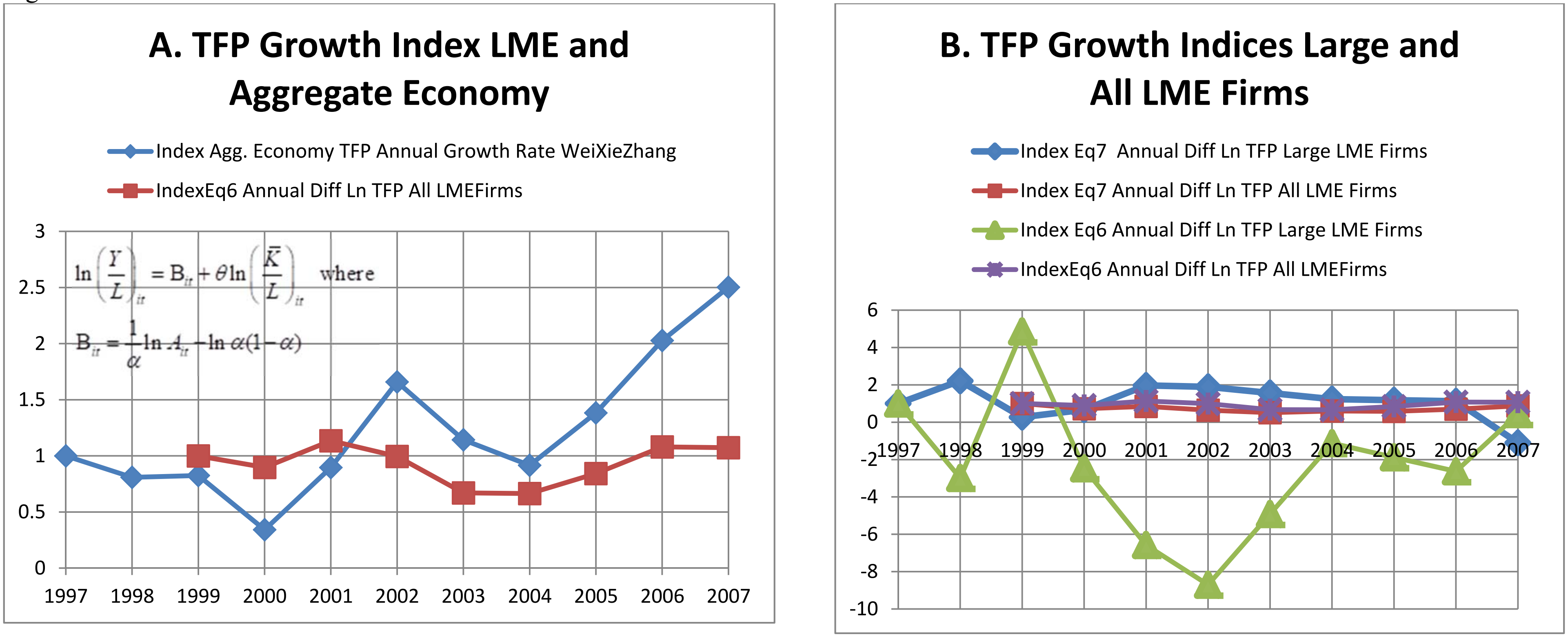
Figure 9 TFP Growth Indices



Source: Authors' calculations. LME index based on coefficients of year dummy variables estimated where the simplified equation (7) is specified as illustrated in panel A. B_{it} includes both county- and year dummy variables. Aggregate economy index based on Wei, Xie, Zhang (2017), data kindly provided by the authors. . Years 2002 and 2004 for Large and Large + Medium samples are interpolated.

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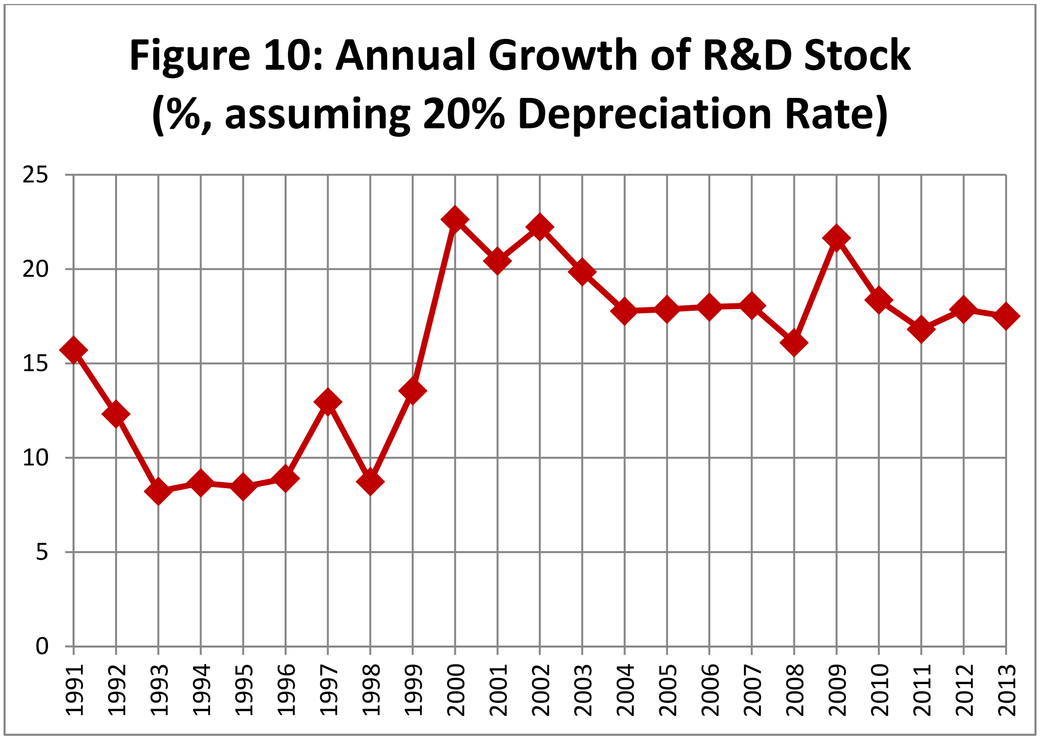
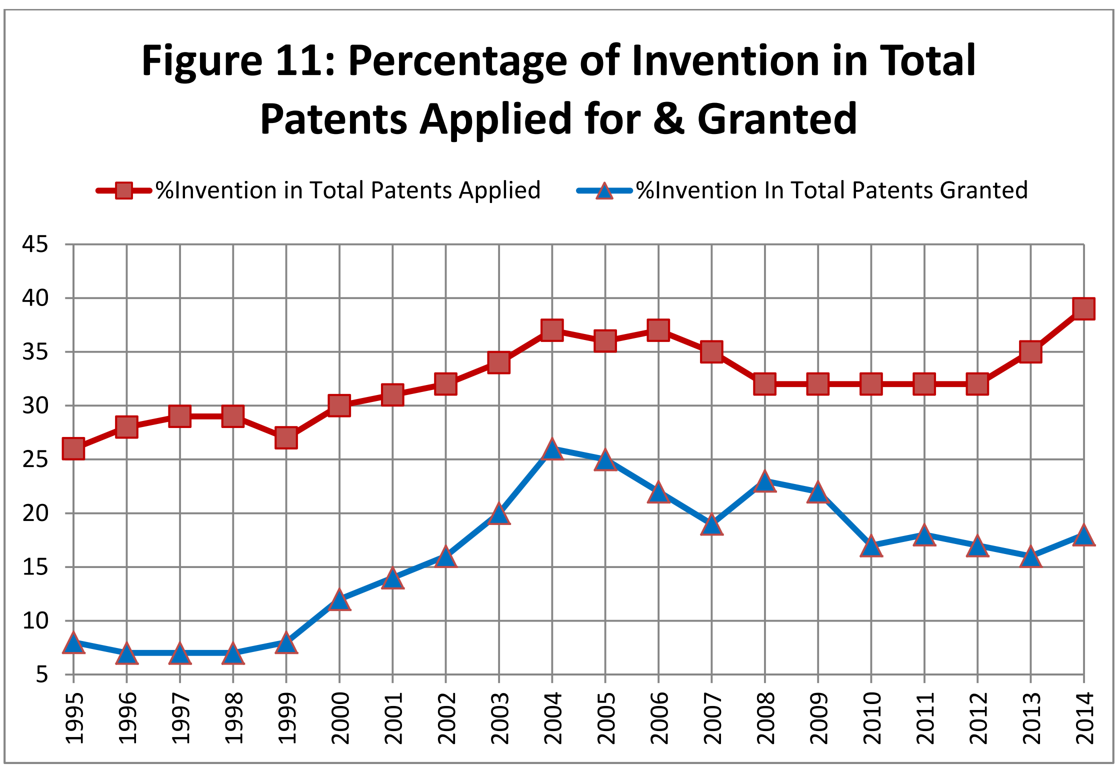
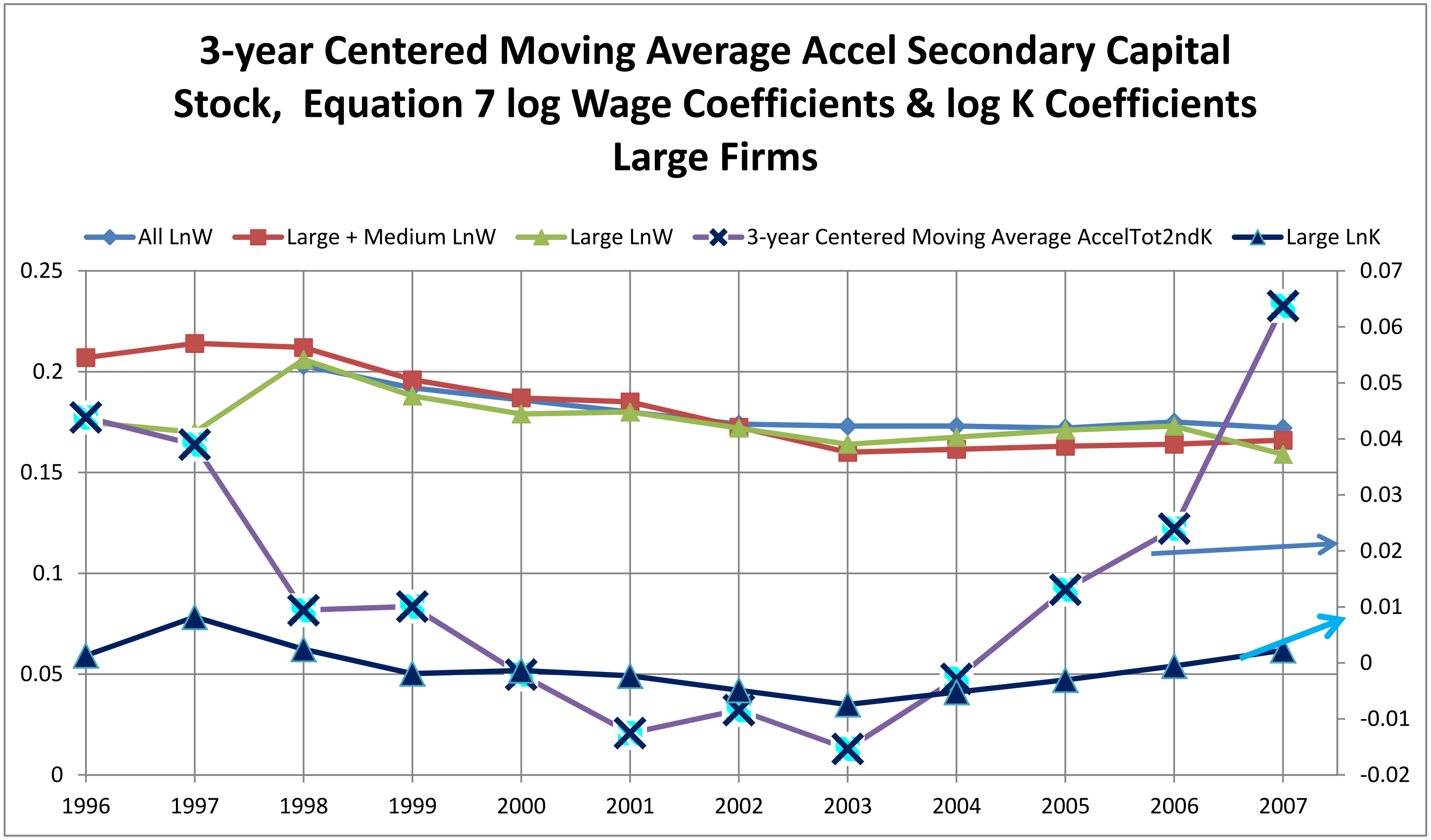


Source: Yu, 2015 & authors' calculations.



Source: Wei, Xie, & Zhang, 2017 Appendix.

Figure 12 Acceleration Secondary Capital Stock and Eq (7) Coefficients



Source: Authors' Calculations

Table 1a Summary Statistics Provincial Data

Variable	Mean	Std. Dev.	Min	Max
Log Secondary Y/L	1.24	0.76	-0.47	3.20
Log Secondary K Stock (t-1)	8.05	0.94	5.89	10.93
Log Wage (t-1)	9.22	0.67	8.13	11.05
Log Primary Emp. (t-10)	6.59	1.07	4.18	8.18
Log K/L (t-1)	2.18	0.71	0.58	4.09
Log R&D Stock (t-1)	4.06	1.59	0.30	7.74
Log FDI Stock (t-1)	12.12	2.08	5.87	16.19

Source: China Statistical Yearbooks, various issues; Wu (2016) and data kindly provided by the author.

Table 1b Summary Statistics 7% trimmed LME data (used in the regression models)

	All				**Large+Medium**				**Large**			
Variable	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max
Log (Y/L)	3.71	0.96	-4.43	12.57	3.59	1.07	-3.99	10.21	3.59	1.13	-2.57	10.21
Log K	8.51	1.75	-3.64	18.64	10.93	1.37	-0.01	18.64	12.18	1.34	3.09	18.64
Log W	2.38	0.68	-5.63	10.80	2.45	0.73	-5.63	9.15	2.47	0.73	-3.33	9.15
Log L	4.80	1.13	0.00	12.17	6.62	0.92	0.00	12.24	7.46	1.12	0.00	12.24
Log (K/L)	3.71	1.32	-8.07	13.85	4.31	1.15	-6.94	12.42	4.72	1.11	-4.60	12.42
N: 1,768,634					N: 207,151				N: 43,778			
Unit of measurement is 1000 Yuan for Y, K, W.												
Year: 1998-2007					Year: 1996-2001, 2003, 2005-2007				Year: 1996-2001, 2003, 2005-2007			

Table 2 Secondary Industry Ln (Output:Labor Ratio*1/Real Wage) Provincial Data Eqn 4a

Levels				First Differences			
Year	$(1-\theta_t)/(1-\theta_0)$	L - 95%	H - 95%	Year	$(1-\theta_t)/(1-\theta_0)$	L - 95%	H - 95%
1978	1.00			1978	1.00		
1979	1.03	0.98	1.07	1979	1.03	0.99	1.07
1980	1.03	0.97	1.09	1980	1.00	0.96	1.04
1981	1.07	1.00	1.13	1981	1.01	0.95	1.07
1982	1.07	1.00	1.14	1982	0.99	0.89	1.08
1983	1.01	0.94	1.08	1983	0.91	0.80	1.02
1984	1.08	0.99	1.16	1984	0.95	0.79	1.12
1985	1.11	1.02	1.20	1985	0.96	0.75	1.18
1986	1.24	1.14	1.34	1986	1.04	0.77	1.32
1987	1.17	1.07	1.27	1987	0.96	0.66	1.25
1988	1.00	0.91	1.10	1988	0.80	0.52	1.09
1989	0.90	0.82	0.98	1989	0.70	0.43	0.98
1990	0.98	0.89	1.06	1990	0.74	0.42	1.06
1991	0.94	0.86	1.02	1991	0.69	0.37	1.02
1992	0.87	0.79	0.96	1992	0.63	0.31	0.95
1993	0.79	0.71	0.88	1993	0.56	0.25	0.87
1994	0.71	0.62	0.80	1994	0.48	0.19	0.77
1995	0.67	0.59	0.74	1995	0.44	0.16	0.73
1996	0.63	0.57	0.70	1996	0.41	0.13	0.69
1997	0.63	0.56	0.71	1997	0.40	0.11	0.69
1998	0.55	0.49	0.60	1998	0.34	0.08	0.59
1999	0.55	0.50	0.61	1999	0.33	0.06	0.60
2000	0.56	0.50	0.61	2000	0.32	0.05	0.60
2001	0.59	0.53	0.65	2001	0.33	0.04	0.63
2002	0.62	0.55	0.69	2002	0.34	0.02	0.66
2003	0.64	0.56	0.72	2003	0.34	0.01	0.68
2004	0.63	0.56	0.71	2004	0.33	-0.01	0.67
2005	0.65	0.58	0.73	2005	0.33	-0.02	0.69
2006	0.71	0.62	0.80	2006	0.35	-0.03	0.74
2007	0.72	0.62	0.81	2007	0.35	-0.05	0.75
2008	0.72	0.62	0.82	2008	0.34	-0.07	0.75
2009	0.75	0.65	0.86	2009	0.35	-0.08	0.77
2010	0.75	0.65	0.85	2010	0.34	-0.09	0.76
2011	0.73	0.63	0.82	2011	0.31	-0.09	0.72

Notes: The level estimates are computed using the following regression model, $\ln\left(\frac{Y_{it}}{L_{it}}\frac{1}{W_{it}}\right) = \phi_t + \eta_i + \varepsilon_{it}$, where $\frac{1-\theta_t}{1-\theta_0} = \frac{1}{e^{\phi_t - \phi_0}}$. The first-difference estimates are computed using the following regression model,

$$\ln\left(\frac{Y_{it}}{L_{it}}\frac{1}{W_{it}}\right) - \ln\left(\frac{Y_{i,t-1}}{L_{i,t-1}}\frac{1}{W_{i,t-1}}\right) = \phi_t + \eta_i + \varepsilon_{it}, \text{ where } \frac{1-\theta_t}{1-\theta_0} = e^{-\sum_{j=1}^{t}\phi_j}.$$

Table 2a Output:Labor Ratio LME Data Eqn 4a

	$\frac{1-\theta_t}{1-\theta_0}$	
	(1)	(2)
1996	1	1
1997	0.963898	1
1998	0.919394	0.873016
1999	0.796706	0.873016
2000	0.758199	0.888889
2001	0.693711	0.936508
2003	0.491202	1.015873
2005	0.507083	1.031746
2006	0.530805	1.126984
2007	0.52838	1.142857
Observations	Large Firms 50,655	Provincial Data 1996 set = 1.0

Notes: See Notes to table 2.

Table 3
Secondary Industry Output:Labor Ratio Provincial Data Eqn 5

	(1)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Log Y/L	Log Wage	Log Y/L˜	Log Wage	Log Y/L˜	Log Wage
Log Wage (t-1)	1.592** (0.012)		1.650*** (0.005)		1.646*** (0.006)	
Log Secondary K Stock (t-1)	-0.130 (0.295)	0.153*** (0.001)	-0.142 (0.194)	0.068 (0.332)	-0.149 (0.179)	0.064 (0.344)
Log R&D Stock (t-1)			0.003 (0.987)	0.057 (0.369)	-0.040 (0.822)	0.027 (0.669)
Log FDI Stock (t-1)					0.043 (0.296)	0.025 (0.134)
Log Primary Emp. (t-10)		-0.156*** (0.005)		-0.238*** (0.003)		-0.226*** (.005)
Constant	- 13.252*** (0.035)	10.530*** (0.000)	- 13.672*** (0.018)	10.788*** (0.000)	- 13.928** (0.016)	10.567*** (0.000)
Observations	604					
R-squared	0.961		0.961		0.961	
Years	1991-2011					
Test Beta = 1 p-val	0.353		0.273		0.283	
Weak ID Stat	6.75		7.66		7.83	

Robust p-values in parentheses
** p<0.01, * p<0.05, * p<0.1

Notes: Dependent variable is augmented with current year flow of R&D investment.

- We assume Secondary K Stock, R&D Stock, and FDI Stock are exogenous
- Our instrument for Log Wage (t-1) is the ten-year lag of total provincial primary employment
- Regressions include year and province fixed effects, and region fixed effects interacted with (current year – 1978)
- Regions are Coast = Fujian, Tianjin, Shandong, Hebei, Beijing, Zhejiang, Hainan, Shanghai, Jiangsu, & Guangdong; Northeast = Jilin, Heilongjiang, & Liaoning; Central = Hubei, Chongqing, Sichuan, Guizhou, Jiangxi, Hunan, In. Mong., Anhhui, Guangxi, Yunnan, Henan, & Shanxi; Far West = Gansu, Qinghai, Tibet, Xinjiang, & Ningxia
- R&D stock are not available for Tibet; FDI stock data are not available for Chongqing or for Tibet in 1992.

Table 4

Secondary Industry Output:Labor Ratio Eqn 7 Provincial Data

	(1)	(2)
	Log Y/L	Log Wage
Log Wage (t-1) x Log K/L (t-1)	0.185**	
	(0.018)	
Log Primary Emp. (t-10) x Log K/L (t-1)		-0.318***
		(0.007)
Log K/L (t-1)	0.659***	1.128***
	(0.000)	(0.004)
Log K Stock (t-1) x Log K/L (t-1)	-0.200***	1.034***
	(0.003)	(0.000)
Constant	-0.168	6.437***
	(0.753)	(0.000)
Observations	642	642
R-squared	0.982	
Years	1991 - 2011	
Weak ID Stat	7.291	

Robust pval in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$