Induced Innovation and Labor Productivity in China

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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, which raises output per unit of employment beyond that which would normally occur through factor substitution under fixed technology. Such innovation would arise from directly from 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 tangible 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 alone 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 and may explain why employment gains appear muted as manufacturing moves or is outsourced to "low-wage" regions and countries (Zhong, 2015).

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 labor saving – raising the production elasticity of capital and the output per unit of labor. 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).

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 discusses the sensitivity of our hypothesis tests to alternative assumptions on the elasticity of substitution; Section 5 very briefly discusses our results in connection with other research on innovation in China, and Section 6 concludes.

2. Data

Our principal source of data is the well-known Large and Medium Enterprises (LME) data base[1], which we supplement with data from official provincial employment and output statistics. Provincial secondary-industry real capital data from the same data used in Wu (2016) have kindly been provided by the author, Yanrui Wu. The LME data are predominantly secondary industry and enable us to match output, 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 1 and 2 present the summary statistics of our basic variables. As indicated in table 2, 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.

Figures 1 and 2 show the growth of real wages between 1983 and 2012 for the provincial data, and between 1997 and 2007 for the LME data, respectively. The economy-wise series contain two series for China's real wage growth, one of them normalized to account for the

[1] This is by far the most comprehensive annual survey of industrial firms conducted by the China National Bureau of Statistics. It includes all state-owned enterprises and non-state owned enterprises with sales over 5 million yuan. The only data base that has a larger sample size is the Economic Census, but that is only conducted once in several years. In 2004 when an Economic Census was conducted, this sample account for about 90% of total sales. This data base is also widely used in the literature, including Song et al. 2011, Hsieh and Klenow 2009, and Brandt et al 2012, to name just a few. 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.

substantial increase in the proportion of workers with at least minimum junior middle school education (see the line with triangle markers in Figure 1). Both the economy-wide and LME data indicate that real wage growth increased abruptly in the late-1990s, declining toward the middle of the next decade, rebounding somewhat around 2005, and remained substantially higher than in the preceding ten years through at least 2012[3]. Figures 3 and 4 illustrate the annual growth of labor productivity. Both the economy-wide and LME data suggest a rising trend that peaks around the turn of the millennium and indicates a rather pronounced decline in the rate of growth after that in the LME data.

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

Our adaptation of the conditions under which labor scarcity encourages technological advances is summarized briefly here and presented in detail in the Appendix.

By adapting Acemoglu's (2010) theoretical framework, we develop a model of wage-induced innovation assuming a unitary elasticity of substitution, which provides the most unambiguous hypotheses for testing whether there has been wage-induced innovation in China. In Section 4 we expand our model to encompass substitution elasticities less than and greater than unity and discuss sensitivity of our findings to this more generalized view.

Unitary Substitution Elasticity Benchmark. The relationship between productivity- and wage growth is unambiguous under the unitary elasticity of substitution specification.

Again, following Acemoglu (2010) we specify the production function of the final good producer:

$$Y = \alpha^{-\alpha}(1-\alpha)^{-1}(K^{\theta}(AL)^{1-\theta})^{\alpha} q(\theta)^{1-\alpha} \,, \qquad \textbf{(1)}$$

where A denotes exogenous labor augmenting technology and $\alpha^{-\alpha}(1-\alpha)^{-1}$ is a convenient normalization further elaborated in the Appendix. The variable $q(\theta)$ denotes the quantity of an

[3] 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).

intermediate good embodying technology θ. A technology θ is created and owned by a profit-maximizing monopolist from which the final good producer purchases technology. This setup allows for induced innovation to operate through an endogenous choice of θ in the final good producer's maximization problem. A positive wage shock not only leads to a standard substitution between capital and labor as in the case of fixed technology but may also induce the final good producer to choose a different production process lessening the impact of rising wage. As shown in the Appendix, we define wage-induced innovation as follows:

$$\frac{\partial \theta^*}{\partial W} > 0, \tag{2}$$

where θ^* denotes the optimal choice of technology. As explained in the Appendix, to ensure the existence of wage-induced innovation in our theoretical model, the wage level should be less than some threshold value that increases with A. This is usually satisfied in the sample period targeted in our study because of a relatively abundant supply of rural workers. The resulting technology level, θ^*, should be greater than 0.5. This is consistent with China's income share data of the industry sector.

Another channel of induced innovation comes from changes in the availability of physical capital or the rental price of capital. We take the availability of physical capital as exogenously determined ($K=\bar{K}$)[4] and define capital-induced innovation as follows:

$$\frac{\partial \theta^*}{\partial \bar{K}} > 0, \tag{3}$$

[4] See Ge & Yang (2014); Bai, Hsieh, & Qian (2006); and Song, Storesletten, & Zilibotti, 2011. Ge & Yang show that their estimation results are robust to the use of an IV procedure. In a recent working paper, Hau and Ouyang (2018) demonstrate persuasively that exogenous variation in the price of real estate diverts saving from flowing to investment in manufacturing firms, raises capital costs for privately held firms without state-enterprises privileged access to funding and significantly and substantially reduces investment local markets where real estate available for local development is curtailed by physical constraints and local government policies. The result is quantitatively important reduction in investment in localities with relatively rapid increases in real estate prices.

The impact of the rental price of capital on induced innovation can be equivalently defined as in (3) if the endogenous-technology relationship between capital stock and its rental price is negative.

Labor Productivity Growth and Real Wage Growth. In the Appendix, we derive the relationship between labor productivity and the real wage as follows:

$$\frac{Y}{L} = \frac{1}{\alpha(1-\theta)} W \quad . \tag{4}$$

Under fixed technology, θ is constant, which implies that labor productivity and the real wage should grow at the same rate. However, under induced technological change, θ increases in response to rising wages. To explore this relationship, we define $\phi = \ln\left(\frac{1}{\alpha(1-\theta)}\right)$. Dividing both sides of (4) by W, and taking logs, we can characterize the behavior of θ over time as:

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

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

Based on equation (4a), under induced technological change, rising wage implies that θ_t is greater than θ_0: the ratio $\frac{1-\theta_t}{1-\theta_0}$ should be less than 1. We estimate equation (4a) using LME data and report regression results based on the subsample of the Large enterprises in figure 5, panel A and results for the provincial data covering the years 1987-2010 in panel B. 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.

Formal Hypotheses Controlling for Omitted Variables. The simple relationship between productivity and wage growth represented in equation (4a) may yield a biased view of technical change due to omission of variables correlated with both the real wage and 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:

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

Under endogenous technical change, $\frac{\partial \theta^*}{\partial \bar{K}} > 0$ and $\frac{\partial \theta^*}{\partial W} > 0$. Thus, we test for endogenous technical change under the following null hypotheses that induced technical change is absent:

Hypothesis (5).1: $\beta = 1$ (indicating $\frac{\partial \theta^*}{\partial W} = 0$)

Hypothesis (5).2**:** $\delta = 0$ (indicating $\frac{\partial \theta^*}{\partial \bar{K}} = 0$)

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 by substituting the optimal demand for labor into (4) and then taking logs and adding location and date identifiers, to obtain[5]

$$\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \theta \ln\left(\frac{\bar{K}}{L}\right)_{it}. \quad \textbf{(6)}$$

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[6]:

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[5] $\bar{K}$ is assumed predetermined as an accumulation of prior investments as in Ge and Yang (2016) and thus is not endogenous with current *W*. If there is no wage-induced technical change, then a change in *W* will impact *Y*/*L* only through reducing amount of labor per unit of $\bar{K}$ along the isoquants of an exogenously given production function.

[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 because the cost function to produce technology θ can be specified in many different ways. 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:

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

Based on this specification, specify the following null hypotheses, indicating that induced technical change is absent:

***Hypothesis (7).1*:** $\gamma_1 = 0$ (indicating $\frac{\partial \theta^*}{\partial W} = 0$)

Hypothesis (7).1: $\gamma_2 = 0$ (indicating $\frac{\partial \theta^*}{\partial \bar{K}} = 0$)

Empirical Results: Tests with LME data. We report regressions of three sets of the LME data based on firm size as defined in the survey documentation: (i) Large enterprises; (ii) Medium and Large enterprises; (iii) All enterprises. 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).

Estimation results for hypotheses on β and γ_1 are reported graphically in panels A and B, respectively of figures 6 and 7[7]. Estimates for δ and γ_2 are reported in figure 8.

In 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 predetermined as discussed above. We include county-

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

$\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \alpha_t \ln\left(\frac{K}{L}\right)_{it} + \gamma_t \ln W_{it} \cdot \ln\left(\frac{K}{L}\right)_{it} + m(K_{it} \text{ or } \ln K_{it}) \cdot \ln\left(\frac{K}{L}\right)_{it} + \varepsilon_{it}$ (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 in tabular form with statistical significance of coefficients are available on request.

and year-fixed effects, as well as regional trend variables as additional controls. The extremely large LME sample size contributes to highly significant estimated regression coefficients and permits the estimation of individual year interactions with both the wage and capital stock variables.

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 assuming unitary elasticity of substitution is strongly rejected for these two subsamples over the period 1996-2001.

The estimated value of β for the full sample that includes 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.

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 than it had been.

Empirical Results: Tests with Provincial data. The provincial data at our disposal encompass years 1991-2011 compared to 1996-2007 covered by the LME data. We explore the behavior of productivity over this longer time period by estimating equation (5) with year- and regional fixed effects as well as region-specific time trends to capture exogenous shocks to TFP. Estimation results are reported in table 3. 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[8].

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.

In contrast to a broad literature[9] 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).

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.

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).

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[8] 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.
[9] Much of this literature is summarized in An (2017).

4. Sensitivity to the Assumption of Unitary Elasticity of Substitution

To evaluate the sensitivity of our hypotheses to a non-unitary substitution elasticity we turn to the CES production function under fixed (exogenous) technology. The firm's problem is

$$\max_{K_t, L_t} \; (\theta K_t^{\rho} + (1-\theta)(A_t L_t)^{\rho})^{(1/\rho)} - W_t \cdot L_t - R_t \cdot K_t \qquad \textbf{(8)}$$

where the parameter A_t denotes labor augmenting technology and the elasticity of substitution between capital and labor is $1/(1-\rho)$. From the first-order conditions, we solve for the profit-maximizing inputs of L and K and derive the following equation:

$$L_t = \theta^{\frac{1}{\rho}} \frac{K_t}{A_t} \left(\left(\frac{W_t}{(1-\theta)A_t} \right)^{\frac{\rho}{1-\rho}} - (1-\theta) \right)^{\frac{-1}{\rho}} . \qquad \textbf{(9)}$$

From (9) and the CES production function, we derive the output-labor ratio:

$$\frac{Y_t}{L_t} = \left(\frac{W_t}{(1-\theta)A_t} \right)^{\frac{1}{1-\rho}} A_t . \qquad \textbf{(10)}$$

Our null hypotheses (absence of induced innovation) on the relationship between labor productivity and wage growth under fixed technology depend critically on the elasticity of substitution. The parameter β is our estimate of the partial derivative of $\ln(Y_t/L_t)$ with respect to $\ln(W_t)$, and the relationship of our obtained estimate of β to the elasticity of substitution is shown in equation (11 as:

$$\widehat{\beta} = \frac{\partial \ln(Y_t/L_t)}{\partial \ln(W_t)} = \frac{1}{1-\rho} \qquad \textbf{(11)}$$

Next, we examine the values of γ_1 implied by the CES production. Under fixed technology, the capital share parameter, θ, is assumed to be invariant to wage increases.[10]. Given the firm's production function, we can re-write the output-labor ratio:

$$\frac{Y_t}{L_t} = \left(\theta (K_t/L_t)^{\rho} + (1-\theta) A_t^{\rho} \right)^{(1/\rho)} . \qquad \textbf{(12)}$$

[10] If the elasticity of substitution differs from one, the capital share parameter is not equal to the capital income share in general.

We focus on the partial derivative of $\ln(Y_t/L_t)$ with respect to $\ln(K_t/L_t)$ and how it is related to changes in the real wage as reflected in our parameter of interest, γ_1. We define the partial of $\ln(Y_t/L_t)$ with respect to $\ln(K_t/L_t)$ as ξ_t and derive it from equation (12) as follows:

$$\xi_t = \frac{\partial \ln(Y_t/L_t)}{\partial \ln(K_t/L_t)} = \frac{1}{H_t}, \text{ where } H_t = 1 + \frac{1-\theta}{\theta}\left(\frac{A_t L_t}{K_t}\right)^{\rho}. \qquad \textbf{(13)}$$

We relate γ_1 to the partial derivative of ξ_t with respect to $\ln(W_t)$, specified as follow:

$$\frac{\partial \xi_t}{\partial \ln(W_t)} = \frac{\rho}{1-\rho}\frac{1}{H_t^2 G_t^2}(1-\theta)^{\frac{1-2\rho}{1-\rho}}\left(\frac{W_t}{A_t}\right)^{\frac{\rho}{1-\rho}}, \text{ where } G_t = \left(\frac{W_t}{(1-\theta)A_t}\right)^{\frac{\rho}{1-\rho}} - (1-\theta). \qquad \textbf{(14)}$$

If we estimate regression models (5) and (7) using the data generated from CES production functions under fixed technology, the predictions of the coefficient estimates based on equations (11) and (14) are:

(i) under unitary elasticity of substitution: $\beta = 1$ and $\gamma_1 = 0$,

(ii) for elasticity of substitution < 1: $\beta < 1$ and $\gamma_1 < 0$,

(iii) for elasticity of substitution > 1: $\beta > 1$ and $\gamma_1 > 0$.

None of these predictions is fully consistent with our empirical findings if we assume that the elasticity of substitution is constant throughout our period of study: (1) β is greater than 1 in the late 1990s but drops below one in the early 2000s; and (2) γ_1 is positive with a rising trend in the late 1990s and remains positive but with a declining trend afterwards. If we were to assume (without additional support in the data or in the literature) that the elasticity of substitution declined from significantly greater than unity to significantly less than unity after 2000 we could "explain" the behavior of β but not the parallel behavior of γ_1 which remains positive after 2000 instead of becoming negative as would be case under scenario (ii) above.

Evaluation of our empirical results is further complicated by the relationship of the parameters β and γ_1 to the degree of induced innovation. Our estimate of β with respect to $\ln(W_t)$ will reflect an additional wage impact under induced innovation as shown below:

$$\hat{\beta} = \frac{\partial \ln(Y_t/L_t)}{\partial \ln(W_t)} = \frac{1}{1-\rho} + \frac{1}{1-\rho}\frac{1}{1-\theta}\frac{\partial \theta}{\partial \ln(W_t)} > \frac{1}{1-\rho}. \qquad \textbf{(15)}$$

Without knowing the functional form of $\theta(W_t)$, it is difficult to predict the value of the right hand side of (15), even for a given value of ρ. However, equation (15) indicates that β increases with induced innovation compared to the case with fixed technology.

To derive the implications of induced innovation for γ_1, we modify equation (14) similarly to equation (11), obtaining:

$$\frac{\partial \xi_t}{\partial \ln(W_t)} = \frac{\left(\frac{W_t}{(1-\theta)A_t}\right)^{\frac{\rho}{1-\rho}}}{H_t^2 G_t^2} \frac{\partial \theta}{\partial \ln(W_t)} - \frac{\rho}{1-\rho} \frac{1}{H_t^2 G_t^2} (\frac{W_t}{A_t})^{\frac{\rho}{1-\rho}} (1-\theta)^{\frac{-\rho}{1-\rho}} \frac{\partial \theta}{\partial \ln(W_t)} . + \frac{\rho}{1-\rho} \frac{1}{H_t^2 G_t^2} (1-\theta)^{\frac{1-2\rho}{1-\rho}} (\frac{W_t}{A_t})^{\frac{\rho}{1-\rho}} \quad \textbf{(16)}$$

In contrast to the implication in equation (15) that induced innovation raises β monotonically, equation (16) yields the possibility of a nonmonotonic relationship. This uncertainty arises from the two additional components on the right-hand-side of equation (16), the first of which is always positive, leading to a higher value of γ_1 with increasing induced innovation. However, the sign of the second component depends on the value of ρ; γ_1 decreases in value under induced innovation when the substitution elasticity is greater than unity but increases γ_1 when the substitution elasticity is less than unity.

The regression analysis will become even more complicated because equation (7) is correctly specified only when the elasticity of substitution is equal to unity. Model misspecifications could also affect the coefficient estimates beyond equations (15) and (16). To help visualize the ambiguity in the impact of induced innovation under the alternative specifications of the substitution elasticity and alternative levels of induced innovation, we perform a simple Monte Carlo simulation experiment. The data-generating process is described in Table 5. We assume there are 50 regions in each pseudo data set. In each region, wage and the supply of capital stock are exogenously determined, generated from a uniform distribution between 1 and 2. A_t is considered as a regular technological progress, widely available to all regions. We normalize A_t to be one.[11] θ is set to be $0.5 + x \cdot W_t$, where we use x to control the degree of induced innovation.[12] Setting x to zero turns off induced innovation. In each data set, we consider three elasticity scenarios: (i) elasticity < 1 (ρ takes a random draw from a uniform distribution between -0.8 and -0.2); (ii) elasticity = 1 ($\rho = 0$); and (iii) elasticity > 1 (ρ takes a random draw from a uniform distribution between 0.2 and 0.8). For each elasticity scenario, we generate 1000 pseudo data sets.

Simulation results are summarized in Figure 9. The upper panel of Figure 9 presents the boxplots of β estimates, while the lower panel presents the boxplots of γ_1 estimates. Table 6 provides a summary of the predicted signs of β and γ_1 for substitution elasticities σ less than, equal to, and greater than 1.0 under fixed technology (x = 0), and wage-induced technology (x > 0). We note the following in our empirical results:

i. The combined estimates of β and γ_1 reported in figures 6 and 7 before 2002 are consistent with induced technology if σ is equal to or less than 1.0 and with fixed technology if σ exceeds 1.0. (We note that the confidence interval for γ_1 is broad enough not to preclude a roughly constant time path for $\gamma_1 > 0$ prior to 2002.)

ii. Following the year 2001, the behavior of β is still consistent with induced technology for the elasticity of substitution that is less than 1.0. Although the γ_1 estimates remain positive after 2001, they tend to decline, particularly after 2005, suggestive of a decline in the degree of wage-induced technology.

In our empirical work, we test the hypotheses that $\beta > 1$ and $\gamma_1 > 0$ to discern whether there has been wage-induced technology in China during our sample period. The results we find prior to 2002 are consistent with both of these hypotheses under the assumption that the elasticity of substitution is equal to or less than 1.0. However, they are also consistent with a scenario in which technology is fixed and the elasticity of substitution between capital and labor is greater than one. To determine which of these scenarios is most consistent with our empirical results, it

[11] A_t could take a different value in a different time period. The qualitative conclusion of our simulation results are unchanged under different values of A_t.

[12] This is a simple shortcut to introduce induced innovation without specifying a full structure of the model to endogenize the choice of θ.

is instructive to compare the *changes* in our estimated β and γ_1 with the theoretical results expanded in this section. After 2002, our estimate of β falls below one, while our estimate of γ_1 declines but remains positive. The joint behavior of β and γ_1 is not consistent with the assumption of fixed technology and a constant substitution elasticity. Under fixed technology, the decline in β after 2001 could be explained by a decline in σ from a value greater than one to a value less than one (which we find implausible). However, this would also imply that γ_1 is negative at the end of our sample period when in fact, our estimated γ_1 remains positive. Evaluation of our empirical results in comparison with the above scenarios leads us to rule out the possibility of fixed technology during our entire sample period.

5. Comparison with Other Evidence on Innovation

We find the absence of evidence supporting wage-induced innovation following China's WTO accession surprising on its face, and also in light of evidence that the productivity (TFP) growth was boosted by WTO 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 10 where we examine 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) exhibits less variation between years except for 2006-2007, suggesting a modest contribution of induced innovation to conventionally measured 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 suggesting 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.

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 11 and 12 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 12, the proportion of invention patents in total patent applications 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 13 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.

6. Summary and Conclusion

We implement a model developed in Acemoglu (2010) 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 readily 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 that supports wage-induced innovation before 2002 but not afterwards. 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 adjustments to the increased competitive environment in the years following WTO entry redirected attention toward general efficiency considerations at least temporarily.

Our null hypotheses are 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, and 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 after 2001. 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

Setup:

- 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 (2010) M economy, 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 rising wage affects the advancement of induced technological changes. The supply of *K* is fixed at $\bar{K}$.

Final-Good Producer

The objective function of the final-good producer:

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

θ: technology

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

χ: price of the intermediate good

A: labor augmenting technology

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

FOCs:

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

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

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

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

$$W = \alpha^{1-\alpha}(1-\alpha)^{-1}(1-\theta)\left(K^{\theta}(AL)^{1-\theta}\right)^{\alpha-1} K^{\theta} A^{1-\theta} L^{-\theta} q(\theta)^{1-\alpha}$$

$= \alpha^{1-\alpha}(1-\alpha)^{-1}(1-\theta)\left(K^{\theta}(AL)^{1-\theta}\right)^{\alpha-1}K^{\theta}A^{1-\theta}L^{-\theta}[\alpha^{-1}\chi^{-1/\alpha}\left(K^{\theta}(AL)^{1-\theta}\right)]^{1-\alpha}$

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

⇨ $L = KA^{\frac{1-\theta}{\theta}}\left(\frac{1-\theta}{1-\alpha}\frac{1}{W}\right)^{\frac{1}{\theta}}\chi^{\frac{\alpha-1}{\alpha\theta}}$

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

The Profit-Maximizing Monopolist

Assumptions:

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

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

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 $\frac{1-\alpha}{1-\alpha+\alpha\theta}$.

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

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

⇨ $\chi = 1$

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

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

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

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

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

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

It is easy to show that the LHS of the FOC is positive given $(1-\alpha)\frac{W}{A} > 1$ and its RHS is positive 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 $\frac{\partial^2 \frac{\theta}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{A}{W}\right)^{(1-\theta)/\theta}}{\partial W \partial \theta} > 0$.

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

$\frac{\partial^2 \frac{\theta}{1-\alpha+\alpha\theta}\bar{K}\left(\frac{1-\theta}{1-\alpha}\frac{A}{W}\right)^{\frac{1-\theta}{\theta}}}{\partial W \partial \theta} > 0$ requires that $W < \frac{1-\theta}{1-\alpha}Ae^{\frac{\alpha\theta^2}{1-\alpha+\alpha\theta}+\frac{\theta}{1-\theta}}$. It is easy to show that $\frac{1-\theta}{1-\alpha}Ae^{\frac{\alpha\theta^2}{1-\alpha+\alpha\theta}+\frac{\theta}{1-\theta}}$ is strictly increasing in θ. Then, we define W_{max} as $\frac{1-0.5}{1-\alpha}Ae^{\frac{\alpha\times 0.5^2}{1-\alpha+\alpha\times 0.5}+\frac{0.5}{1-0.5}}$, which should be larger than $\frac{A}{1-\alpha}$. 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) $\frac{A}{1-\alpha} < W < W_{max}$ (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.

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

Given $\frac{A}{1-\alpha} < W < W_{max}$, it is easy to show that $\frac{1-\alpha}{1-\alpha+\alpha\theta}+\frac{1}{\theta}\ln\left(\frac{W(1-\alpha)}{A(1-\theta)}\right)-1 > 0$. 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

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

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

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

$$=\frac{W}{\alpha(1-\theta)}$$

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

Summary of the Model

(i) Given $\bar{K}$, 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 $\bar{K}$: an increase in $\bar{K}$ 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 $\bar{K}$ fixed). 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.

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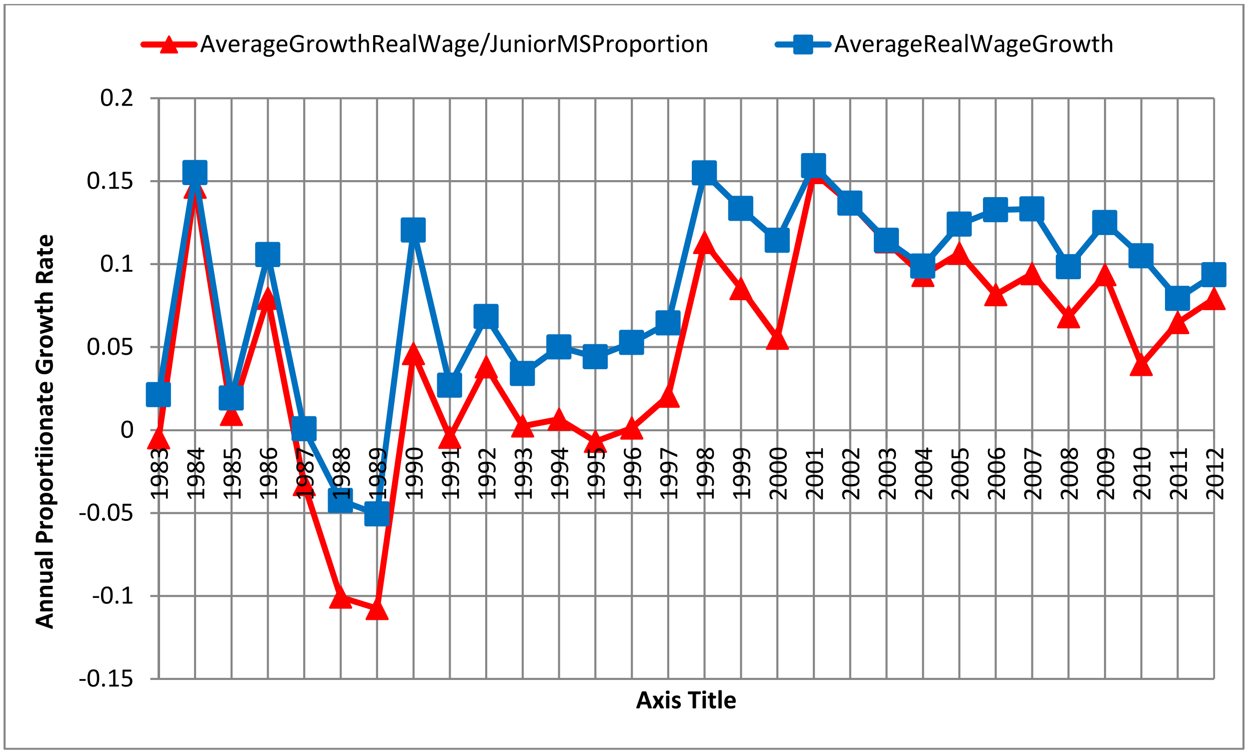
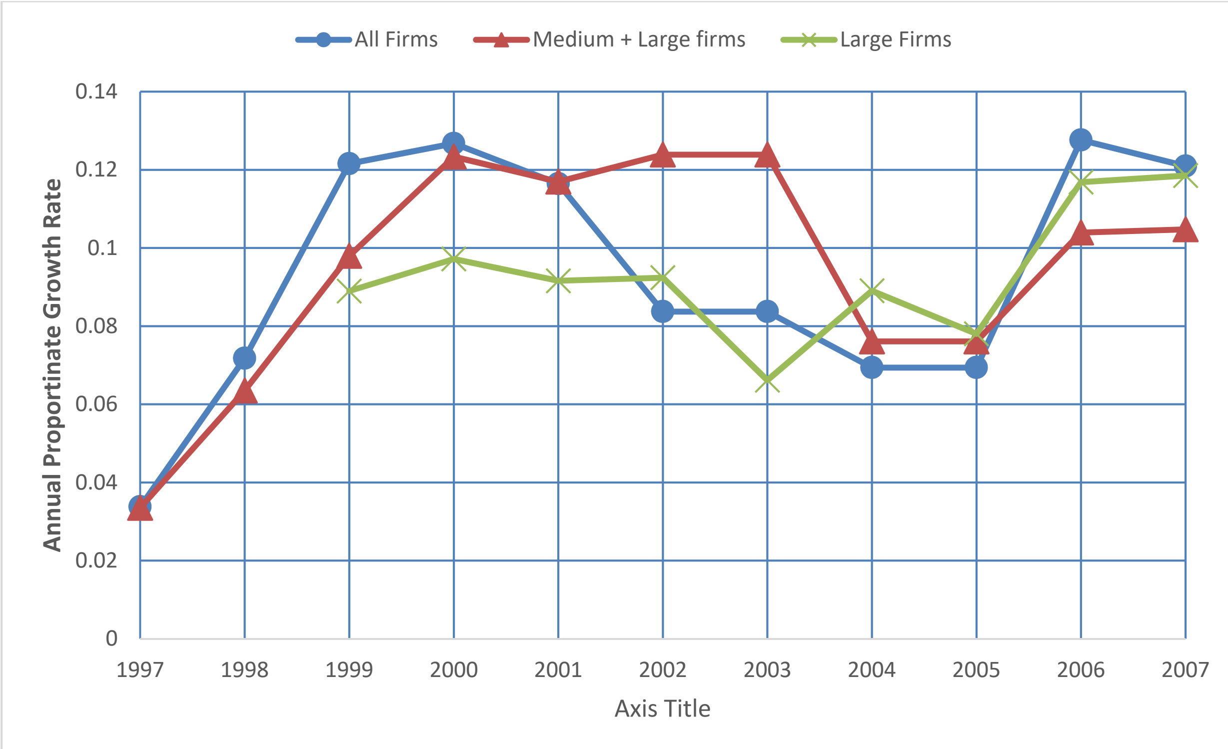
Figure 1. Provincial Data: Average Real Wage Growth



Source: Authors' calculations from China Statistical Yearbooks

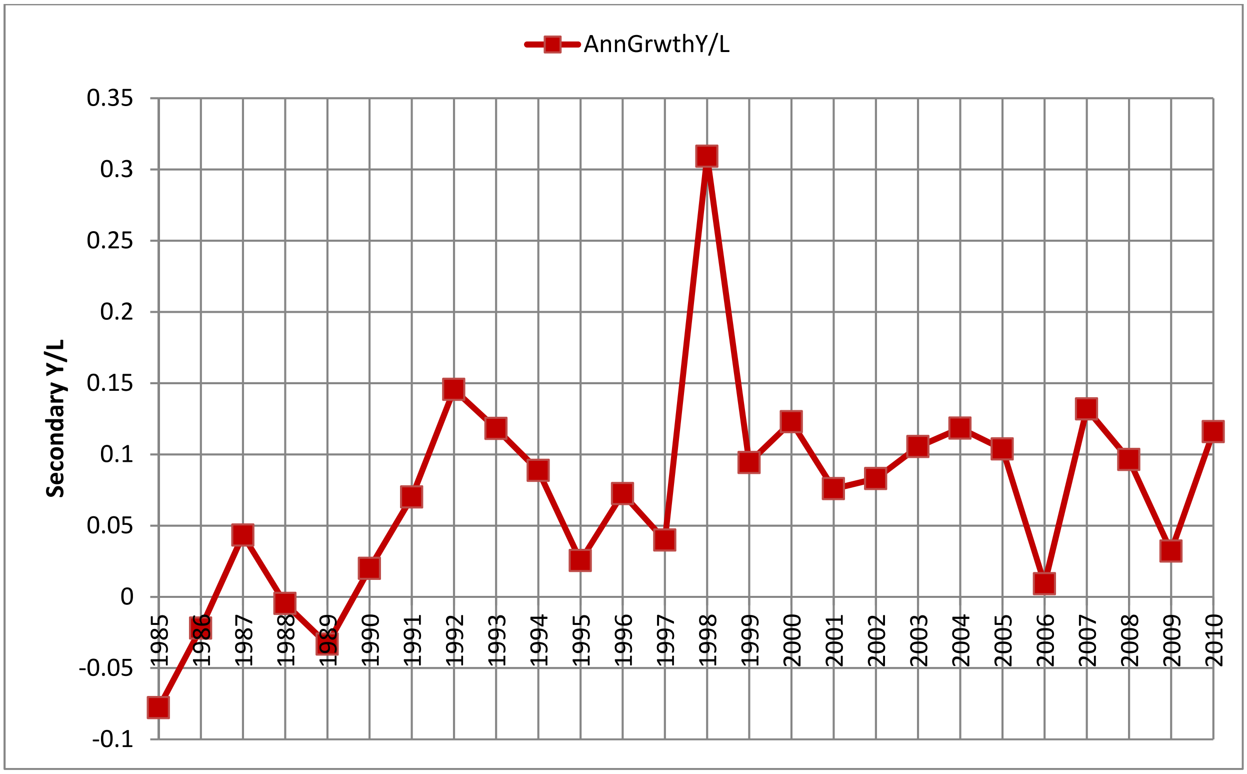
Note: Data are provincial averages of proportionate real wage growth in secondary industry and provincial averages of proportionate growth of real wage in secondary industry divided by proportion of workforce that has graduated from junior middle school or higher.

Figure 2. Large & Medium Enterprises: Real Median Wage Growth



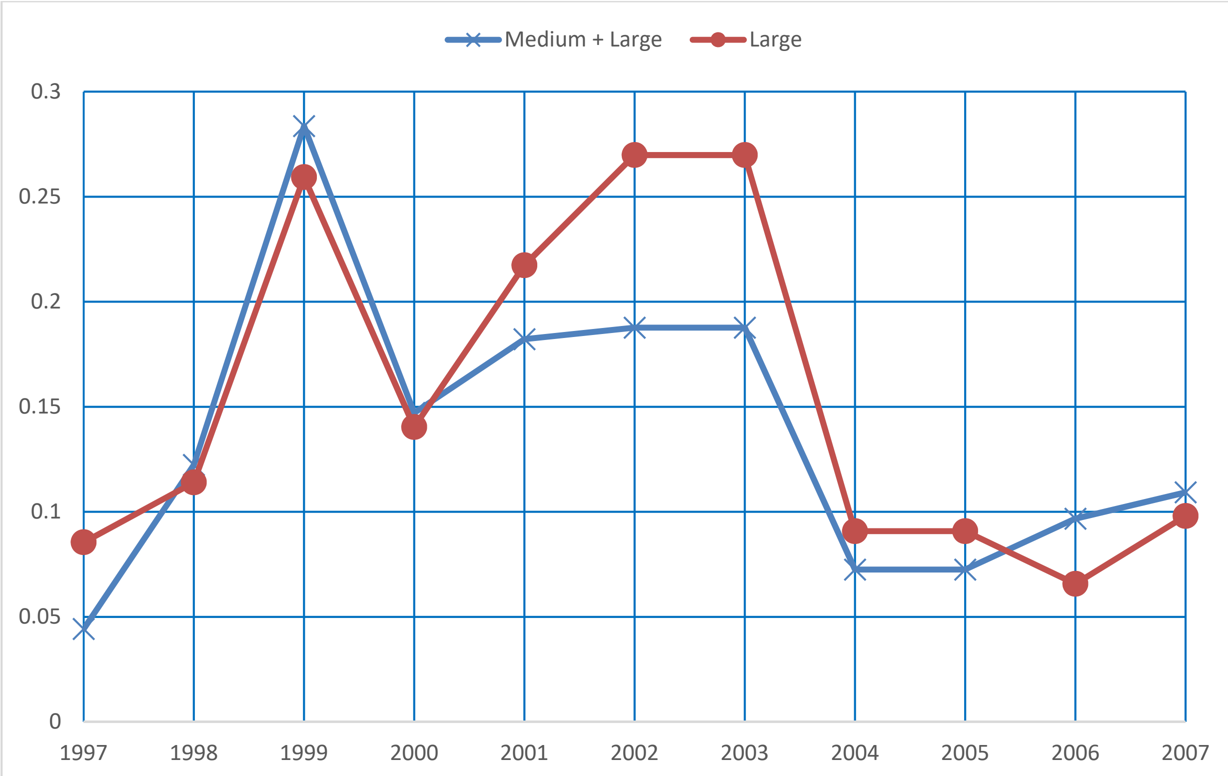
Source: Author calculations from LME data. Series show annual proportionate growth of median firm real wages.

Figure 3. Provincial Data: Secondary Industry Labor Productivity Growth



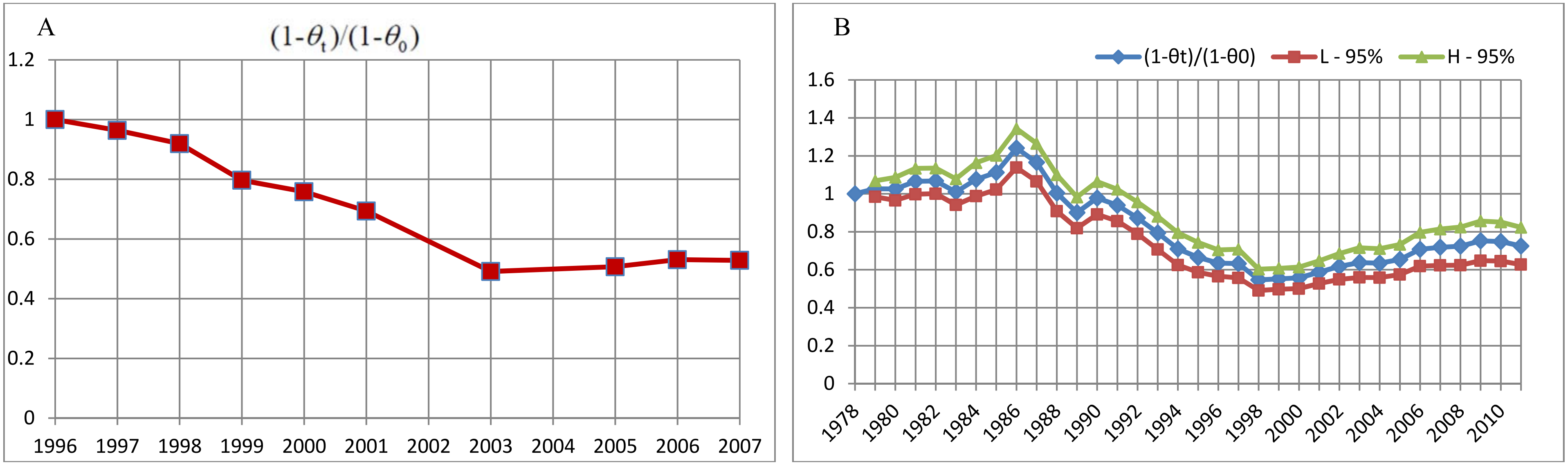
Source: Authors' calculations from China Statistical Yearbook

Figure 4. Large & Medium Enterprises: Median Labor Productivity Growth



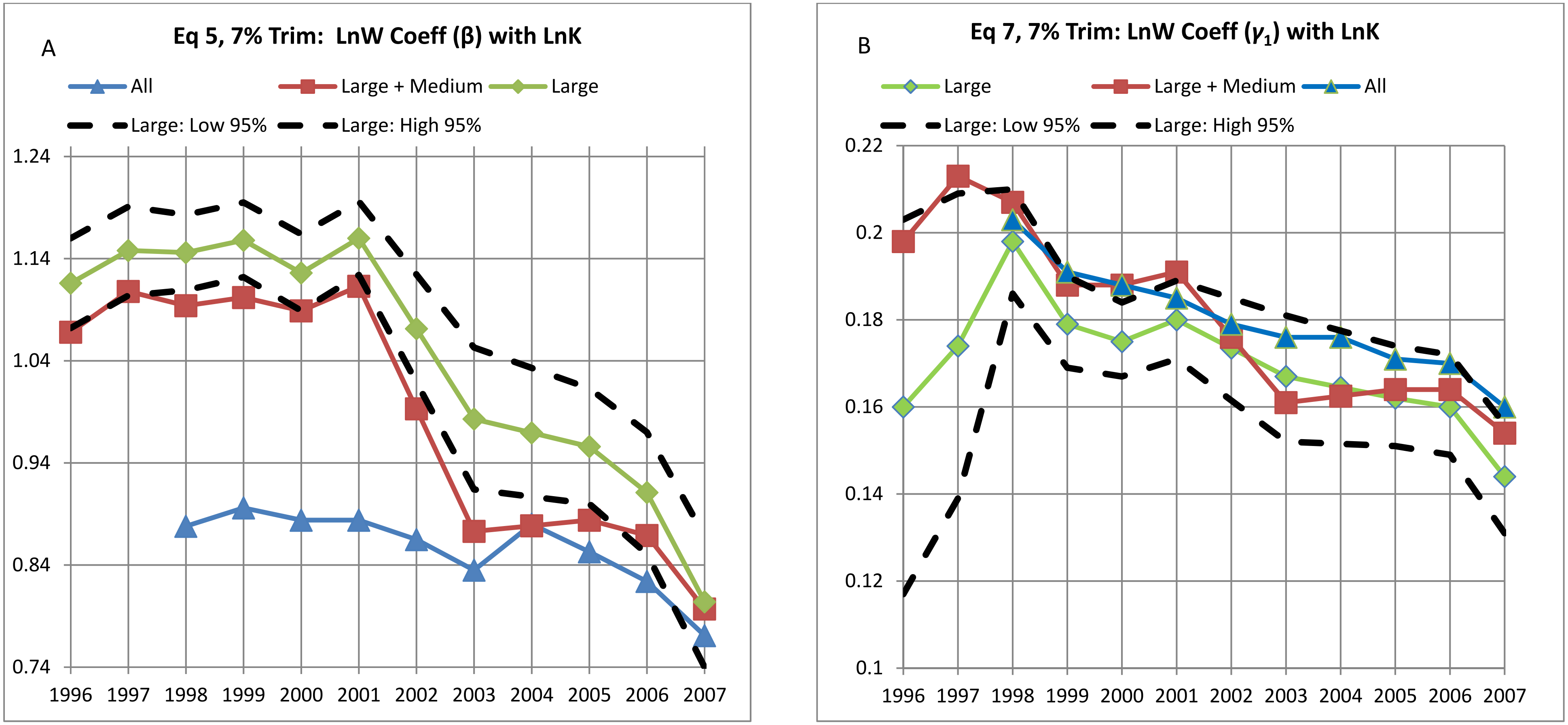
Source: Authors' calculations from LME data.

Figure 5. Estimates of Equation (4a)



Note: Panel A LME data; Panel B Provincial data.

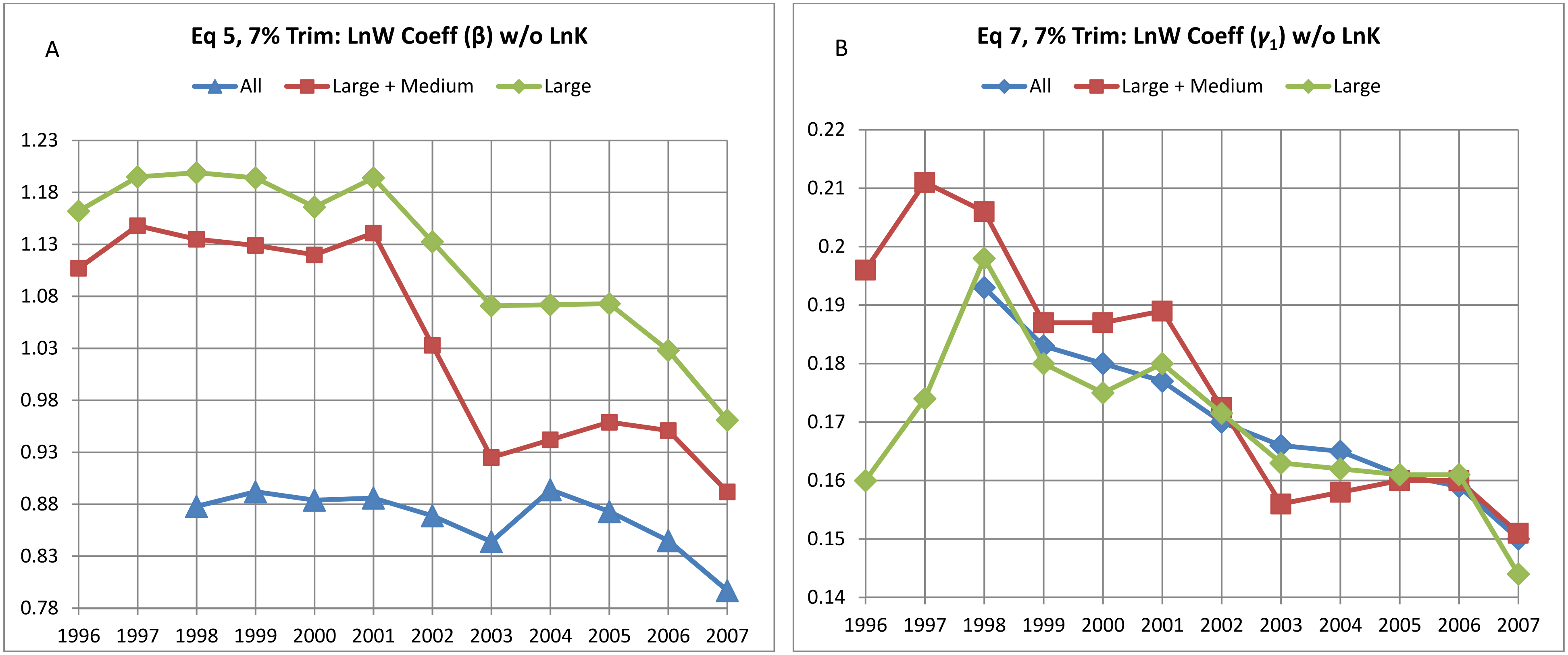
Figure 6. Estimates of β and γ_1 with $Ln\overline{K}$ in Equations (5) and (7)



Notes: Authors' calculations from LME data.

Years 2002 and 2004 for Large and Large + Medium samples and their confidence intervals are interpolated.

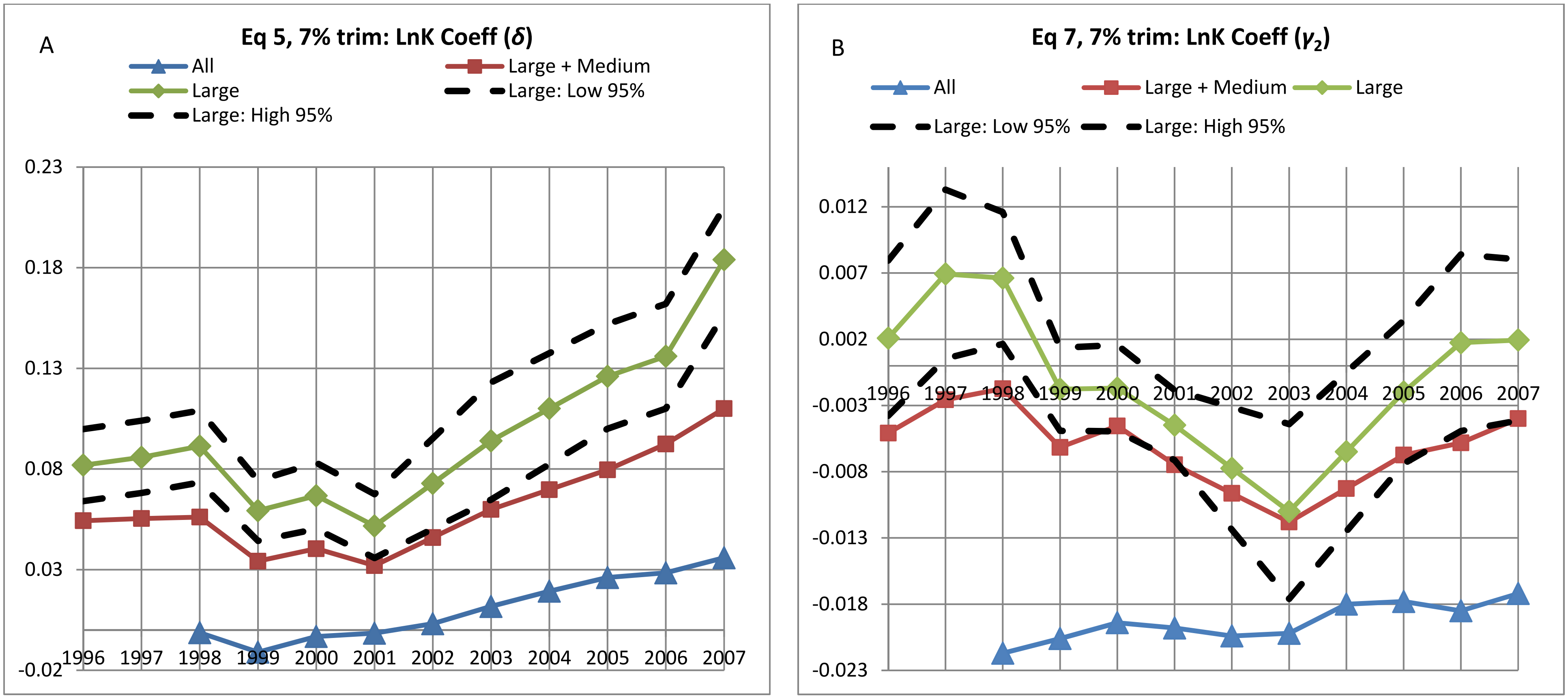
Figure 7. Estimates of β and γ_1 without $Ln\overline{K}$ in Equations (5) and (7)



Notes: Authors' calculations from LME data.

Years 2002 and 2004 for Large and Large + Medium samples and their confidence intervals are interpolated.

Figure 8. Estimates of δ and γ_2



Notes: Authors' calculations from LME data.

Years 2002 and 2004 for Large and Large + Medium samples and their confidence intervals are interpolated.

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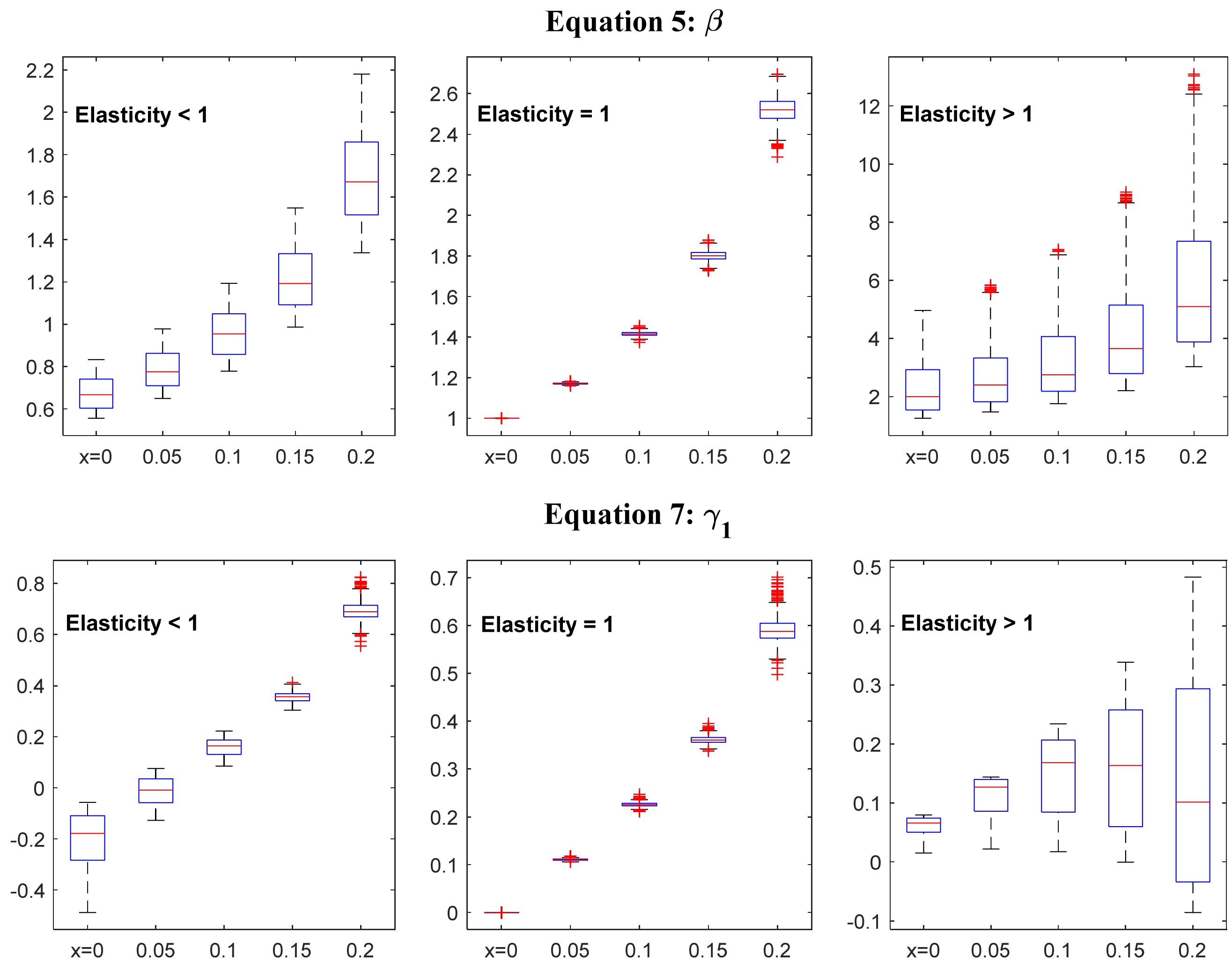
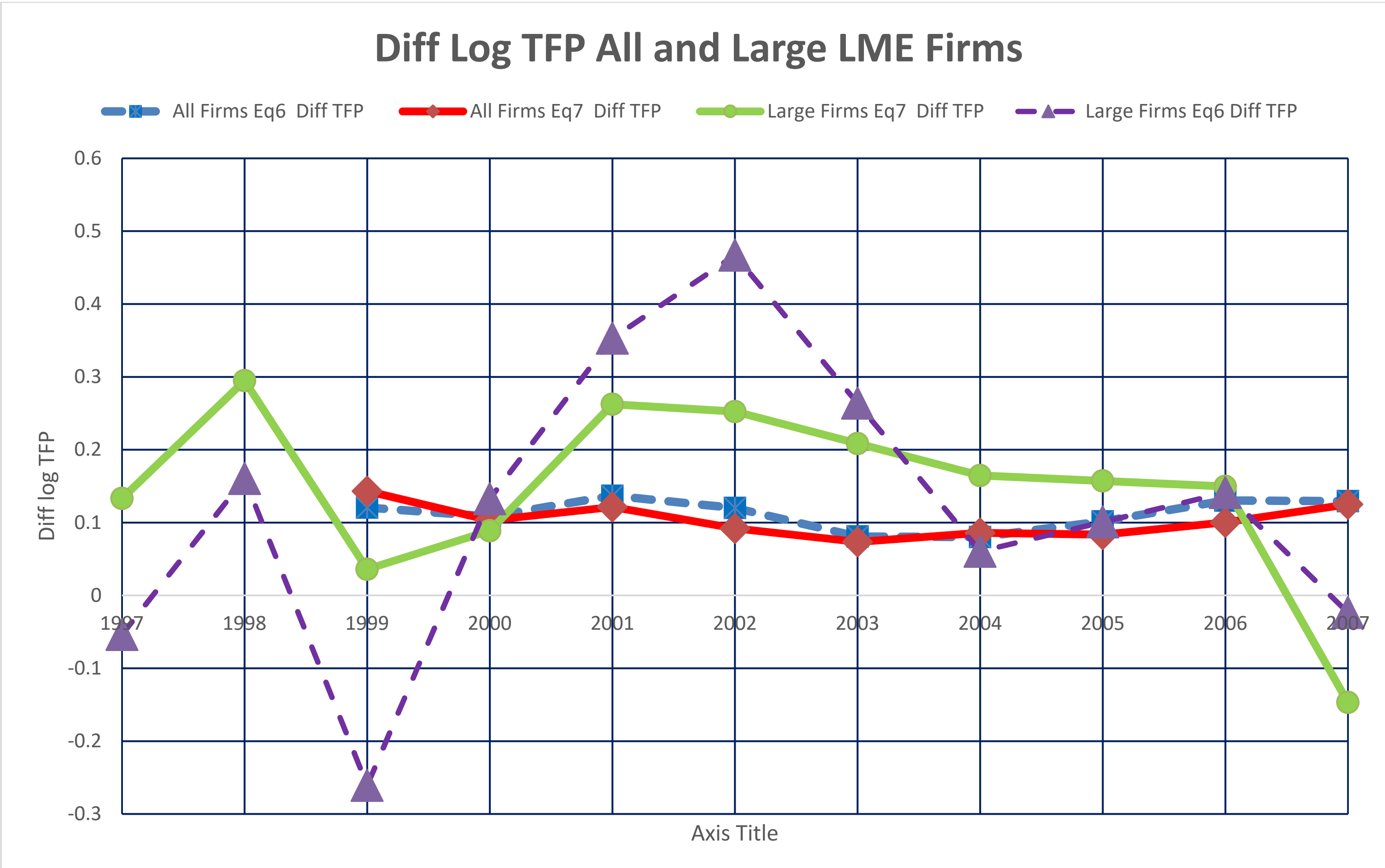
Figure 9 Monte Carlo Simulation Results



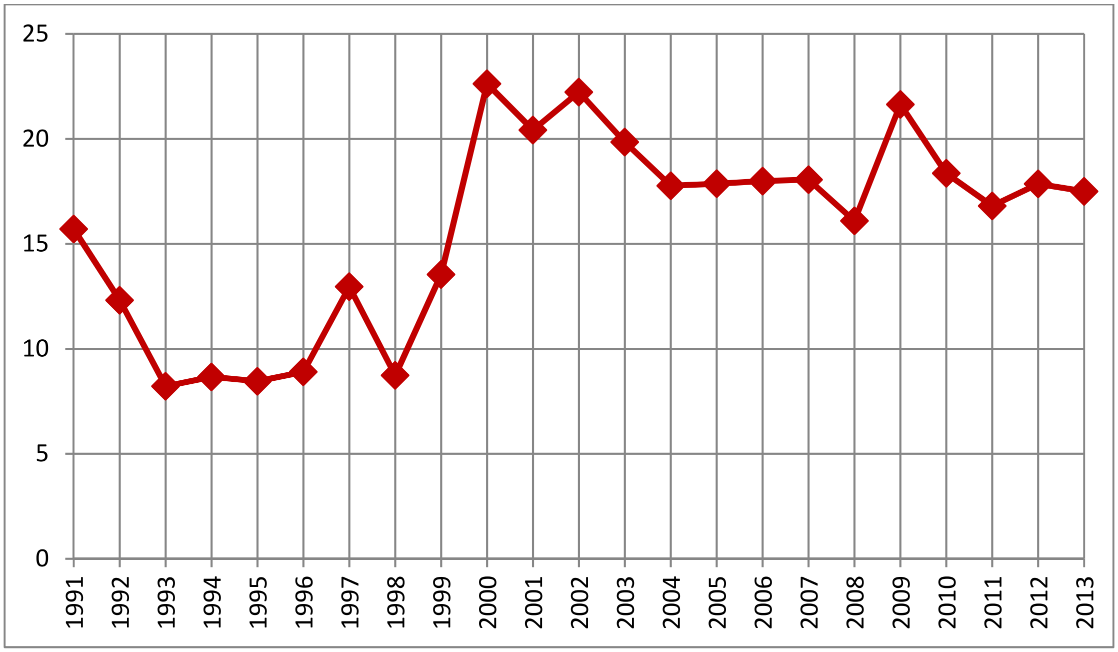
Note: In each boxplot, the median is indicated by the central mark; the 25th and 75th percentiles are indicated by the bottom and top edges of the box, respectively; the outliers are marked by the '+' symbol.

Figure 10. TFP Growth



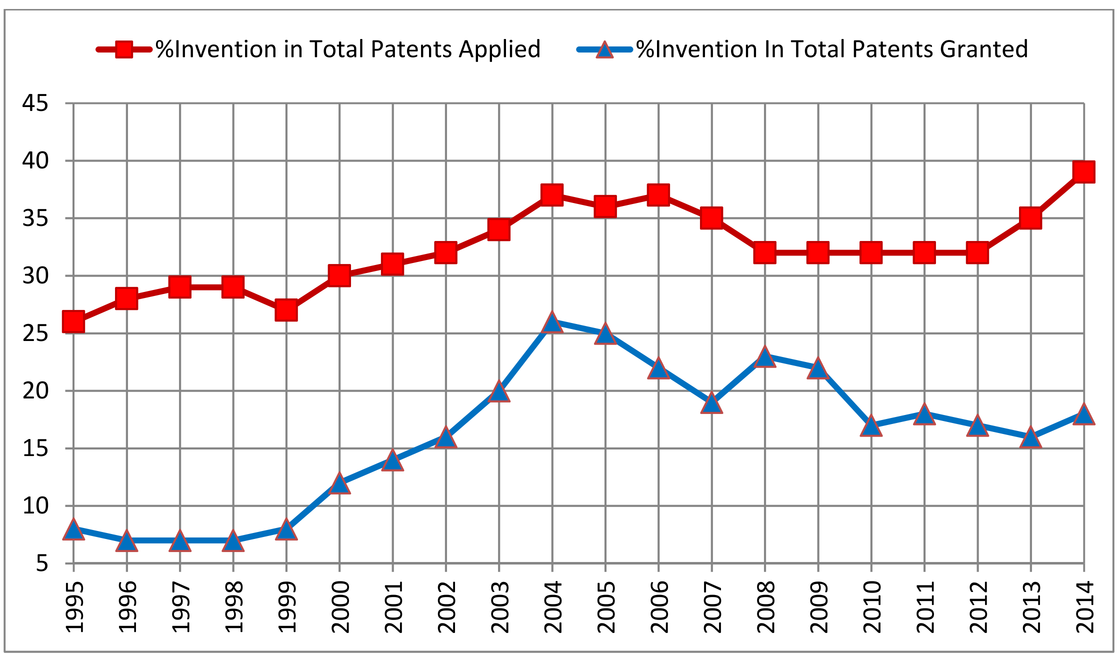
Notes: Authors' calculations from LME data. Log TFP is based on coefficients of year dummy variables estimated from equations (6) $\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \theta \ln\left(\frac{\bar{K}}{L}\right)_{it} + \varepsilon_{it}$. and (7) $\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \gamma_0 \ln\left(\frac{\bar{K}}{L}\right)_{it} + \gamma_1 f(W_{it}) \ln\left(\frac{\bar{K}}{L}\right)_{it} + \gamma_2 f(K_{it}) \ln\left(\frac{\bar{K}}{L}\right)_{it} + \varepsilon_{it}$ Years 2002 and 2004 for Large and Large + Medium samples are interpolated.

Figure 11. Annual Growth of R&D Stock (%)



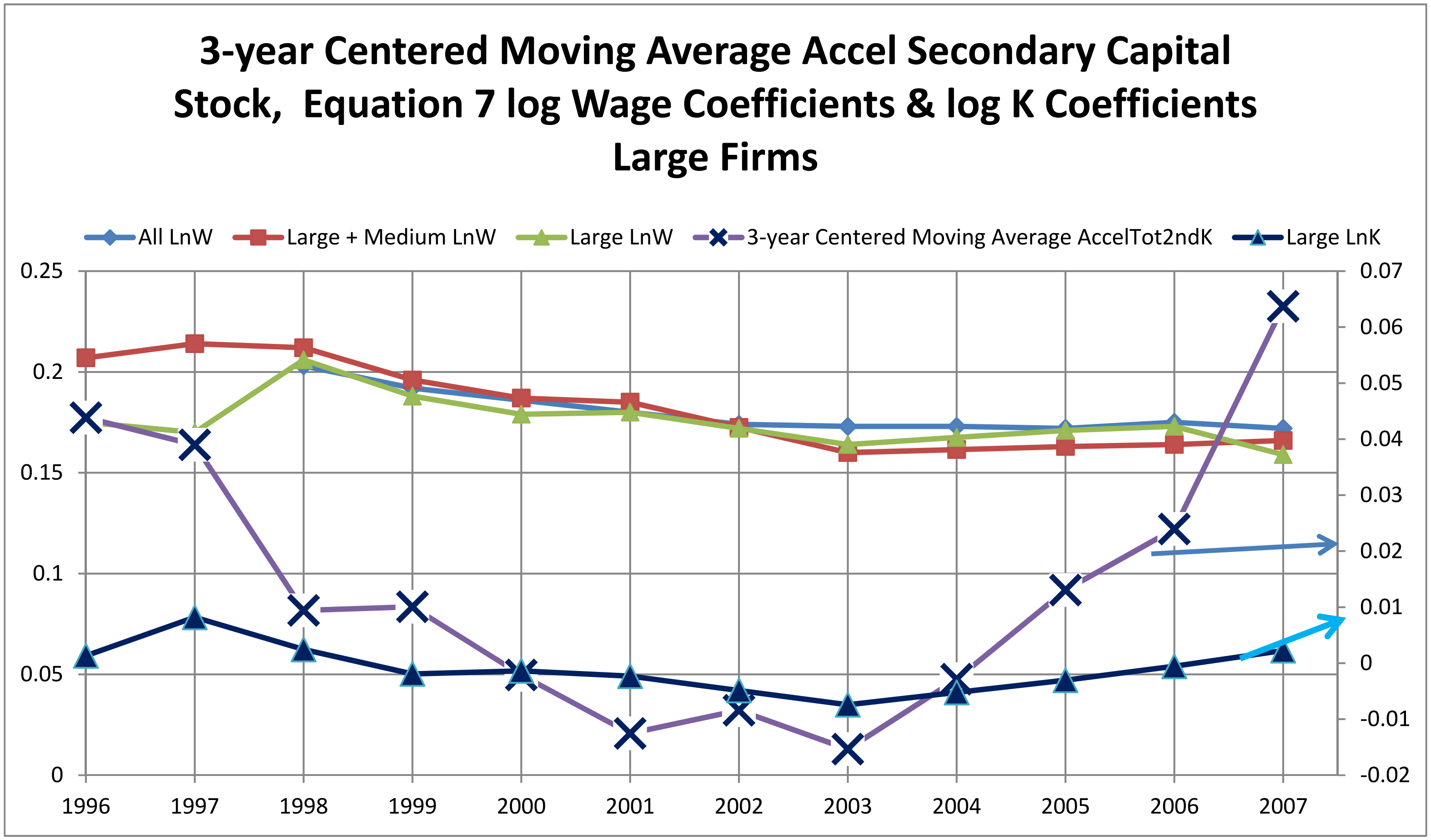
Source: Authors' calculations.

Figure 12. Percentage of Invention in Total Patents Applied for & Granted



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

Figure 13 Acceleration Secondary Capital Stock and Eq (7) Coefficients



Source: Authors' Calculations.

Table 1 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 provincial secondary-industry real capital data are kindly provided by the author.

Table 2 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 3
Secondary Industry Output:Labor Ratio Provincial Data Eqn 5

	(1)	(2)	(3)	(4)	(5)	(6)
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 p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5
Monte Carlo Simulation – Parameter Values

W_t	Uniform (1,2)
K_t	Uniform (1,2)
ρ	Elasticity of Substitution > 1: Uniform (0.2, 0.8) Elasticity of Substitution < 1: Uniform (-0.8, -0.2) Elasticity of Substitution = 1: 0
θ	$0.5 + x \cdot W_t$
A_t	1

Table 6
Theoretical Predictions of β and γ_1

Assumed Substitution Elasticity	Elasticity < 1		Elasticity = 1		Elasticity > 1	
Parameters	β	γ_1	β	γ_1	β	γ_1
Fixed Technology (x=0)	< 1	< 0	1	0	> 1	> 0
Induced Technology (x>0)	$\frac{\partial\beta}{\partial x} > 0$, starting from $\beta<1$	$\frac{\partial\gamma_1}{\partial x} > 0$, starting from $\gamma_1<0$	$\frac{\partial\beta}{\partial x} > 0$, starting from $\beta=1$	$\frac{\partial\gamma_1}{\partial x} > 0$, starting from $\gamma_1=0$	$\frac{\partial\beta}{\partial x} > 0$, starting from $\beta>1$	$\frac{\partial\gamma_1}{\partial x} \lesseqgtr 0$, starting from $\gamma_1>0$