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ABSTRACT

Induced Innovation: Evidence from China's Secondary Industry

We investigate the effect of rising labor costs on induced technological change in China's secondary industry. While previous studies have focused primarily on induced technology change in agriculture and in energy production/environmental protection, there has been little evidence relating to China's adjustments as rising labor costs affect its global competitiveness in the manufacturing sector. Building on insights developed in a rich literature, we propose a model linking changes in labor productivity to changes in labor costs, 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. These hypotheses are tested using both firm- and provincial-level data. Our empirical results support the hypothesis that rising wages have induced labor-saving innovation 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 Classification: O30, D22, D24, D33

Keywords: induced innovation, labor productivity growth, China

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1. Introduction

Focusing on China's secondary industry, we address the question of whether rising labor costs have stimulated labor saving technological innovation, raising output per unit of employment beyond what would normally occur through factor substitution under fixed technology. To our knowledge, this question has not yet been investigated for industries outside agriculture and energy production and environmental protection in the Chinese economy. Whereas previous studies dealing with China's aggregate economy have documented evidence of China's achievements in innovation as reflected in research and development (R&D) investments and in successfully applying for patents[1], our approach seeks tangible evidence of successful innovation by examining the link between rising wages and labor productivity growth. By linking evidence of innovation to changes in domestic wages, we build on insights developed in Atkinson & Stiglitz (1969) and Acemoglu (2015). This work complements research that assumes technical change to be exogenous, as in Molero-Simarro (2017), Ge and Yang (2014), Bai and Qian (2010) and many other well-known publications they cite.

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). We follow the more recent work of Acemoglu (2010, 2015) and Acemoglu and Autor (2011), and propose a model of endogenous technology adoption in response to changing wages. 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 standard factor substitution under fixed production parameters.

We find evidence confirming the presence of wage-induced innovation that is particularly strong in the last decade of the 20th century and that more pronounced among the largest firms. We recognize that our modelling and empirical testing of the wage-induced innovation hypothesis is sensitive to assumptions regarding the elasticity of substitution between capital and labor. We perform simulation exercises to evaluate the robustness of our conclusions and to evaluate our estimation results assuming that labor and capital are either gross complements or substitutes. The results of these simulations provide further evidence that we have identified the presence of factor-price-induced technological innovation and its time trend.

[1] T noteworthy examples are Hu and Jefferson (2009) and Wei, Xie, and Zhang (2017)

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

Tables 1 and 2 present the summary statistics of our basic variables. Our principal source of data is the well-known Large and Medium Enterprises (LME) data base[2], which we supplement with data from official provincial employment and output statistics. 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[3]. 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.[4]

To complement the firm-level analysis, we also utilize a province-level data set. The provincial output, wage, employment, R&D, and FDI data come from the NBS annual provincial statistical yearbooks. Provincial secondary-industry real capital data from the same data used in Wu (2016) have kindly been provided by the author, Yanrui Wu. While our output, capital stock, and employment data are sector-specific, we are only able to observe the aggregate provincial wage level. The provincial data allow us to estimate our empirical model over a longer period than the LME data (1991-2011 vs. 1996-2007). The provincial data also have broader coverage than the LME data, the latter including only the subset of firms that were sampled in the

[2] This is by far the most comprehensive annual survey of industrial firms conducted by the National Bureau of Statistics of China (NBS). 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.
[3] Our estimation results are quite robust to the trimming of implausibly extreme values.
[4] The firm size follows the official designation, which may not be entirely aligned with employment or sales.

industrial survey. The provincial data also cover every industry in the secondary sector.[5] Finally, we also use provincial data to implement the instrumental variable technique to address potential endogeneity between output per worker and the wage. Our instrument is the ten-year lag of primary sector employment. Following Lewis (1954), we assume that China had a large "surplus population" in rural areas before market-oriented reforms that supported worker mobility. In Lewis' dual sector model, the larger this "surplus population," the more the industrial sector can grow without significant upward pressure on wages. We use the ten-year lag of primary sector employment as a measure of each province's reservoir of "surplus" workers, which would be a source of exogenous variation in the provincial wage. 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. Both the provincial 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[6]. Figures 3 and 4 illustrate the annual growth of labor productivity. Both the provincial and LME data suggest a decline in the rate of growth in years following the turn of the millennium. The figures show that labor productivity and real wage growth both accelerated in the late-1990s, a result consistent with induced innovation. However, these trends might also reflect standard substitution of other factors (especially capital) for labor in response to the change in relative prices. In the next section 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 theoretical model is an adaptation of Acemoglu's (2010) theoretical framework. The conditions under which rising wages encourage technological innovation in our model are summarized briefly here and presented in detail in the Appendix. Our base model of wage-induced innovation assumes a unitary elasticity of substitution, which provides a benchmark scenario for testing whether there has been wage-induced innovation in China. In Section 4 we

[5] Another significant difference between the LME data and the provincial data is that the former only includes firms whose sales are above 5 million yuan whereas the provincial data also include firms with sales below this mark.
[6] 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, and Monarch (2010) and those in the collection of papers on whether China has passed the Lewis Turning Point in *China Economic Review* (2011).

relax this rather strict assumption and consider substitution elasticities less than or greater than unity and discuss sensitivity of our basic findings to this more generalized view.

Unitary Substitution Elasticity Benchmark. Following Acemoglu (2010) we specify the production function of the final good producer as follows:

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

where A denotes exogenous labor augmenting technology and $\alpha^{-\alpha}(1-\alpha)^{-1}$ is a convenient normalization used in Acemoglu (2010). The variable $q(\theta)$ denotes the quantity of an intermediate good embodying technology θ. K and L denote capital and labor, respectively. The objective function of the final good producer is defined as follows:

$$\max_{K,L,q(\theta)} \alpha^{-\alpha}(1-\alpha)^{-1}\left(K^{\theta}(AL)^{1-\theta}\right)^{\alpha} q(\theta)^{1-\alpha} - W\cdot L - R\cdot K - \chi q(\theta), \tag{2}$$

where W, R and χ denote wage, rental rate of capital and the price of the intermediate good, respectively. 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. As in Acemoglu (2010), we assume K is supplied inelastically at a fixed level $\bar{K}$. W is exogenously given, which allows us to examine how rising wage rates affect the advancement of induced technological changes.[7] 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 to reduce the impact of rising wages.

As shown in the Appendix, we define wage-induced innovation as follows:

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

where θ^* denotes the optimal choice of technology.[8] As explained in Wei et al. (2017), rising wages are an important driver to stimulate China's growth in innovation. A common empirical

[7] The theoretical framework can be easily modified to examine the impact of labor scarcity on induced innovation by assuming labor is supplied inelastically at a fixed level $\bar{L}$, as examined in Acemoglu (2010).

[8] 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. We believe this is a realistic assumption 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: for the industry sector (that is relevant to our provincial and LME data), the labor income share was always less than 0.5 during 1978-2004 (see Table 4 from Bai and Qiang, 2010).

approach to examining the price-induced innovation hypothesis focuses on testing the existence of (lagged) price variables in a production or cost function (e.g., Peeters and Surry, 2000; Caputo and Paris, 2005). Our paper takes a different approach by examining the relationship between labor productivity growth and real wage growth, illustrated in the next subsection.

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

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

Under fixed technology, θ is constant, which implies that labor productivity and the real wage should grow at the same rate. This is a general property of a Cobb-Douglas production function that assumes unitary elasticity of substitution between labor and capital.[9] However, under induced technological change, θ increases in response to rising wages, implying that labor productivity should grow faster than the real wage. The appendix provides a theoretical example of modeling induced technological change, but the relationship between labor productivity and real wage growth is consistent with alternative modeling approaches under the scenario that wage-induced innovation helps utilize labor more efficiently in production, thereby increasing labor productivity.

To explore this relationship, we define $\phi_t = \ln\left(\frac{1}{\alpha(1-\theta_t)}\right)$. Dividing both sides of (4) by W, and taking logs, we can characterize the behavior of θ over time as:

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

where i denotes province i and $\eta_{l(i)}$ captures provincial fixed effects when the provincial data are used; i denotes firm i and $\eta_{l(i)}$ captures county fixed effects when we use the LME data ; ϕ_t denotes year fixed effects, 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.[10] We estimate equation (4a) using the

[9] Exogenous technical changes (A), such as exogenous industrial upgrading, will impact labor productivity and wage rates equally, so their growth rates will remain the same.

[10] It is not appropriate to use equation (4a) to identify θ_0, so we use $(1-\theta_t)/(1-\theta_0)$ to examine how θ_t changes over time.

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 1978-2011 in panel B. Both sets of results indicate accelerating induced technological change in the late 1990s. After that, 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.

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. To deal with these two issues, we take logs of (4) and, adding the year and location identifier (B_{it}), we obtain the following approximations:[11]

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

When using the LME data, we also allow β and δ to be year-specific coefficients. Under wage-induced technical change, we expect $\beta > 1$. Thus, we test for wage-induced technical change under the following null hypothesis:

Null Hypothesis: $\beta = 1$ (in the absence of wage-induced technical change)

Alternative Specification. 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 year identifiers, to obtain[12]

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

[11] The optimal choice of technology can be affected by level of capital stock (this can be demonstrated using our theoretical model), so we include capital stock and B_{it} as additional control variables to capture non-wage-induced innovation.

[12] $\bar{K}$ 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 the amount of labor per unit of $\bar{K}$ along the isoquants of an exogenously given production function.

We need to examine whether the technology parameter θ is a function of the real wage. To test this hypothesis, we hold constant the influence of the availability of physical capital (allowing for possible capital-induced innovation) and 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[13,14]:

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

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

***Null Hypothesis*:** $\gamma_1 = 0$ (in the absence of wage-induced technical change)

Empirical Results: Tests with LME data. We report regression results using the three sets of the LME data differentiated by 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).

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.[15] We include county-

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[13] Our key theoretical results shown in equations 5 and 7 are conditioned on capital stock. 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 capital stock in the main text, but we also conducted extensive robustness checks using fractional polynomials and splines. Specifically, we estimated the following specifications:

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

$$\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \alpha_t \ln\left(\frac{\bar{K}}{L}\right)_{it} + \gamma_t \ln W_{it} \cdot \ln\left(\frac{\bar{K}}{L}\right)_{it} + m(\bar{K}_{it} \text{ or } \ln \bar{K}_{it}) \cdot \ln\left(\frac{\bar{K}}{L}\right)_{it} + \varepsilon_{it} \text{ (7')},$$

where *m*(.) is either a fractional polynomial function or a spline function. This allows us to control for a wide variety of trends in capital stock, 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.

[14] Again, when the LME data are used, we allow γ_0, γ_1 and γ_2 to vary by years.

[15] Rising labor cost is closely related to the dynamics of rural-urban migration (Golley and Meng, 2011; Knight et al., 2011, Wang et al., 2011, Zhang et al., 2011). An individual firm has very limited power to influence rural-urban

and year-fixed effects, as well as regional trend variables as additional controls (B_{it} in equations 5 and 7). We hope this can alleviate concern that our results are driven by drastic SOE reforms in the late 1990s as well as their varying impacts across regions. 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. The standard errors are clustered at the county level. Estimation results for hypotheses on β and γ_1 are reported graphically in panels A and B, respectively of figures 6 and 7.[16]

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. This is consistent with our wage-induced innovation hypothesis. However, the estimated value of β 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. These results indicate that wage induced innovation is weak or absent among smaller-size firms.

As shown in figure 6 panel B, the estimated value of γ_1 is above zero through the sample period. After 1998, the time paths of γ_1 are closely parallel for all subsamples of the LME data, dropping substantially through 2003 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 6 panel A, 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.

migration decisions. In the regression models, we include county fixed effects and regional time trends to control for local common factors that could affect both local wage rates and labor productivity.

[16] Estimation results in tabular form are available on request.

The inclusion of a measure of physical capital in equations (5) and (7) serves to control for omitted variable bias in estimates of the impact of wage increases on technical change. Estimates of the coefficients β and γ_1 are very robust to exclusion of the capital-stock variable shown in figure 7.

Empirical Results: Tests with Provincial data. The provincial data at our disposal allow us to test the induced innovation hypothesis over the years 1991-2011 compared to 1996-2007 covered by the LME data. We estimate equation (5) with year and provincial fixed effects as well as region-specific time trends (B_{it} in equations 5 and 7) to capture exogenous shocks to TFP. Estimation results are reported in table 3. To control for the potential problem of endogeneity in the estimation of wage coefficient with provincial aggregate data, we employ the two-stage least squares (2SLS) method, where the instrumental variable (IV) for provincial real wage is the 10-year lagged size of the provincial primary-industry labor force[17].

The point estimates of approximately 1.6 for the coefficients of the one-year lagged log wage are highly significant in both Models (1) and (2) 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 0.32 in Model (1) and 0.33 in Model (2). 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 weaker evidence regarding wage-induced innovation may reflect the fact that provincial data include firms of all sizes. As our LME results show, evidence of induced innovation is stronger in the Large firm group.

In contrast to a broad literature[18] 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 Model (2) 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

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[17] 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. Since our IV is lagged ten years behind our potentially endogenous independent variable, this approach also limits the years for which we are able to estimate the regression model.

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

provincial primary-industry labor force. The estimate of γ_1 in the first row of table 4 is significantly greater than zero regardless of whether the capital-stock variable is included, and thus supports the hypothesis of wage-induced technical change.

The regression results based on both micro (firm-level) and macro (province-level) data indicate that the evidence of wage-induced innovation becomes weaker if we focus on the hypothesis test of β instead of γ_1 (which is consistently positive and significant). This is mainly related to the threshold values (depending on the elasticity of substitution between capital and labor) used in our hypothesis tests. The relationship between β instead of γ_1 is further examined in Section 4 by relaxing the assumption of unitary elasticity of substitution.

4. Relaxing the Assumption of Unitary Elasticity of Substitution

The unitary elasticity of substitution assumption provides us with a clear analytical benchmark to test wage-induced innovation. To evaluate the sensitivity of our hypothesis tests to the existence of non-unitary substitution elasticity we turn to the CES production function. The purpose is to examine threshold values of β and γ_1 that indicate the existence of wage-induced innovation. To identify those threshold values, we first analyze the firm's problem under fixed (exogenous) technology, as defined below:

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

where the parameter A_t denotes labor augmenting technology and the elasticity of substitution between capital and labor is $\frac{1}{1-\rho}$. From the first-order conditions, we solve for the profit-maximizing inputs of L and K and obtain the following result:

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

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:

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

Next, we examine the values of γ_1 implied by the CES production function. Under fixed technology, the capital share parameter, θ, is assumed to be invariant to wage increases.[19] Given the firm's production function, we can re-write the output-labor ratio:

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

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:

$$\xi_t = \frac{\partial \ln(Y_t/L_t)}{\partial \ln(K_t/L_t)} = \frac{1}{H_t}, \quad \textbf{(13)}$$

where $H_t = 1 + \frac{1-\theta}{\theta}(\frac{A_t L_t}{K_t})^{\rho}$. We relate γ_1 to the partial derivative of ξ_t with respect to $\ln(W_t)$, specified as:

$$\frac{\partial \xi_t}{\partial \ln(W_t)} = \frac{\rho}{1-\rho} \frac{1}{H_t^2 G_t^2} (1-\theta)^{\frac{1-2\rho}{1-\rho}} (\frac{W_t}{A_t})^{\frac{\rho}{1-\rho}}, \quad \textbf{(14)}$$

where $G_t = \left(\frac{W_t}{(1-\theta)A_t}\right)^{\frac{\rho}{1-\rho}} - (1-\theta)$. If we estimate regression models (5) and (7), and assuming that the data that are consistent with 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 $\gamma_1 > 0$.

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

No single prediction from above is fully consistent with our empirical findings presented in the previous section. Focusing on the LME results, we find that β is greater than 1 in the late 1990s but drops below one in the 2000s. We also find that 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 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 the case under scenario (ii) above. The assumption with fixed technology is not compatible with our empirical findings regardless of the assumed elasticity of substitution in our CES framework.

If there exists wage induced innovation, our estimate of β with respect to $\ln(W_t)$ will reflect an additional wage impact beyond what is predicted under fixed technology:

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

Without specifying a full model, the functional form of $\theta(W_t)$ is unknown and it is difficult to pin down the threshold value of $\hat{\beta}$ (even for a given value of ρ) to be used in the hypothesis test. However, equation (15) indicates that $\hat{\beta}$ increases with induced innovation compared to the case with fixed technology.

To derive the implications of wage-induced innovation for γ_1, we modify equation (14) to allow for the possibility of a nonmonotonic relationship between wage-induced innovation and the parameter γ_1 as follows:

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

In contrast to the implication in equation (15) that wage-induced innovation raises β monotonically, an uncertainty about the relationship 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 wage-induced innovation, while the sign of the second component depends on the value of ρ. The sign is negative if the substitution elasticity is greater than unity but positive if the substitution elasticity is less than unity.

Under a general CES production function, the regression analysis will become much more complicated, because equations (5) and (7) are 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. The parameter A_t is considered to represent regular technological progress, widely available to all regions. We normalize A_t to be one.[20] θ is set to be $0.5 + x \cdot W_t$, where we use x to control the degree of wage-induced innovation.[21] Setting x to zero turns off wage-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 (ρ = 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 8. The upper panel of figure 8 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 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 the substitution elasticity is equal to or less than 1.0 and with fixed technology if the substitution elasticity exceeds 1.0. (We note that the confidence

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

[21] This is a simple shortcut to introduce wage-induced innovation without specifying a full structure of the model to endogenize the choice of technology.

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.

It is also instructive to compare the *changes* in our estimated β and γ_1 (see figure 6) with the theoretical results presented 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. Under fixed technology, the decline in β after 2001 could be explained by a decline in the substitution elasticity from a value greater than one to a value less than one (which we find implausible). However, this would also imply that γ_1 should be negative at the end of our sample period. 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 that fixed technology prevailed during our entire sample period.

The upshot of this simulation exercise is that our empirical results are fully consistent with gradually declining wage-induced innovation when the elasticity of substitution is less than unity. Previous studies of the elasticity of substitution between labor and capital in China provide evidence supporting our induced innovation hypothesis. For example, Mallick (2012) finds that the elasticity of substitution between capital and labor in China is significantly less than unity. Acemoglu and Restrepo (2019) choose an industry-level elasticity of substitution of 0.8, citing Oberfeld and Raval's (2014) for United States industry. In other words, our hypothesis tests based on the assumption of unitary elasticity of substitution use conservative threshold values to test wage-induced innovation, which may lead to under-rejection of the null hypothesis. However, given the declining trends in both β and γ_1 estimates, it is still reasonable to conclude that wage-induced technology change had a stronger influence on productivity growth in China in the late 1990s than in the 2000s.

5. Comparison with Other Evidence on Innovation

We find the absence of stronger 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 9 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 fixed 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 the patent series between 1999 and 2004. As illustrated in figure 11, 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 they decline slightly through 2011 (for applications) and through 201 (for grants). The leveling off of both 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.

6. Summary and Conclusion

We implement a model developed in Acemoglu (2010) to investigate wage-induced, labor-saving innovation in China's secondary industry. 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. In a more flexible CES framework, we find labor productivity growth could exceed real wage growth under fixed technology if the elasticity of substitution exceeds unity. However, elasticity of substitution exceeding unity is not consistent with published estimates of the elasticity of substitution (Bai and Qian, 2010; Mallick, 2012). More importantly, the assumption of fixed technology is not consistent with the changes in our estimated coefficients over time, strengthening our evidence of wage-induced innovation.

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. However, 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 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. Such an increase in the probability of a Type II error would further strengthen empirical support for the existence of wage-induced technology change. In addition, both of the empirical patterns we find in our regression analysis and the simulated patterns based on a more flexible CES framework support that wage-induced innovation 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.

The industrial explosion that turned China into the "workshop of the world" (Gao, 2012) has contributed to dramatic wage increases. As manufacturers start to look elsewhere in order to maintain international competitiveness, other nations hope investors will be attracted to their low-cost labor, and produce a similar employment boom. However, these hopes might not be realized if China's rising wages have induced substantial labor-saving innovation whereby unit costs are even lower under the new technology than those in lower-wage labor markets. These innovations would imply that the employment impact of expanding output is continually damped by rising productivity (Zhong, 2015).

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. We adopt a similar setup, except that the wage (*W*) instead of the labor supply is given. The goal is to examine how rising wages affect the advancement of induced technological changes. The supply of *K* is fixed at $\overline{K}$ in the short run.

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

The Profit-Maximizing Monopolist

Assumptions:

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

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

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

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

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

⇨ $\chi = 1$

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

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

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

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.

Output (*Y*) Per Worker

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

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

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

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

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.

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) 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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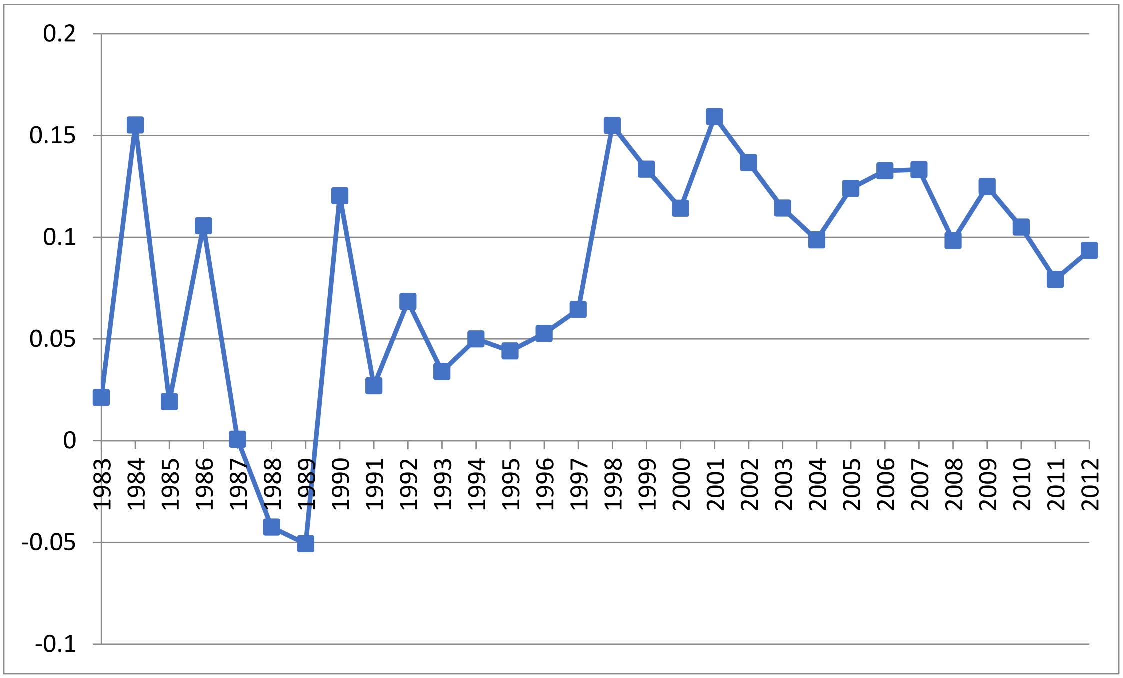
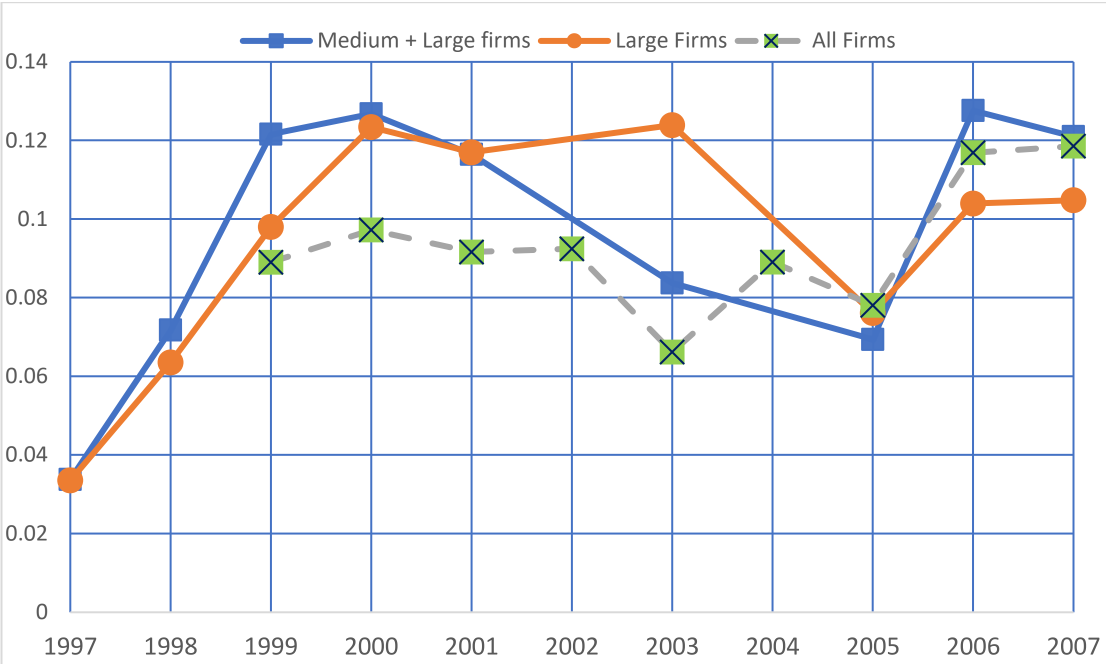
Figure 1. Provincial Data: Average Real Wage Growth



Source: Authors' calculations from China Statistical Yearbooks

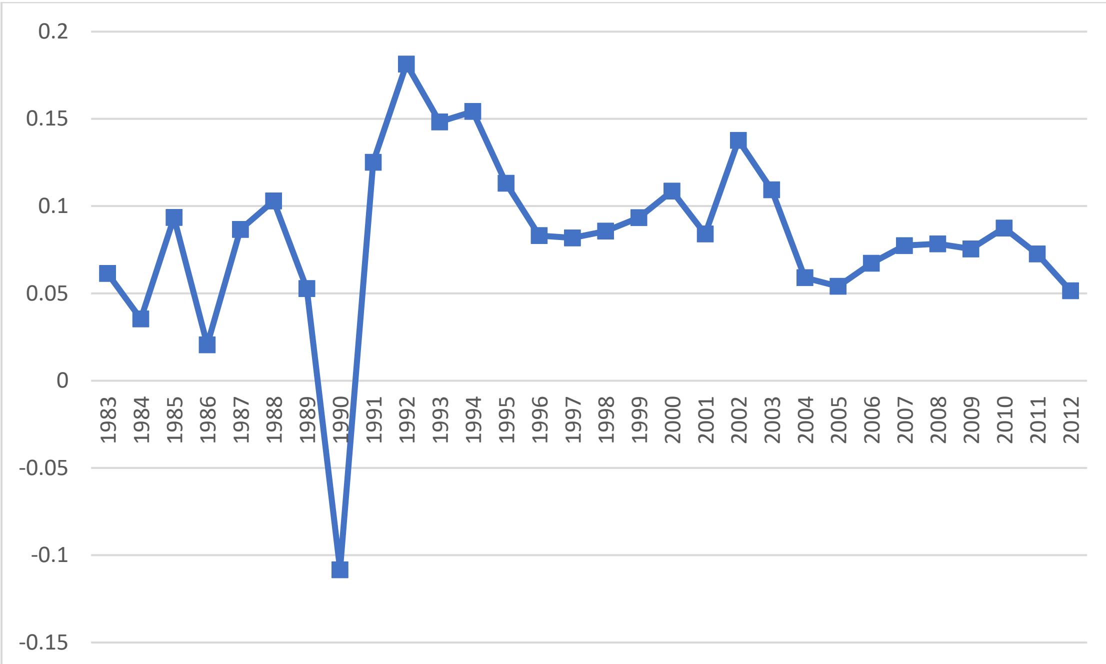
Note: Data are provincial averages of wage growth in secondary industry.

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



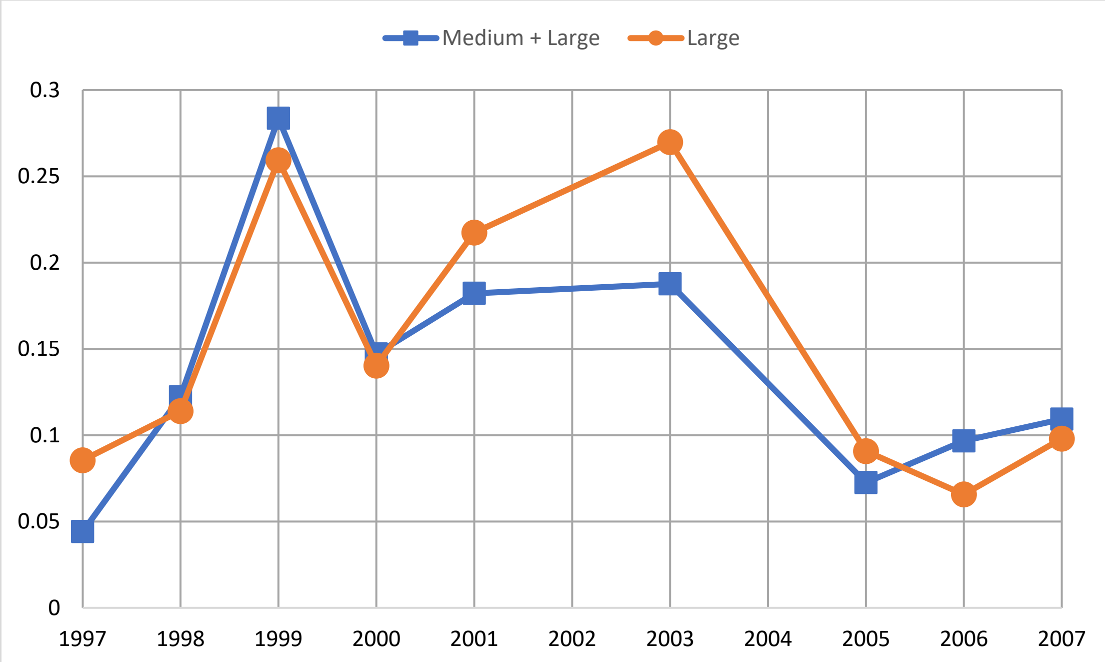
Source: Author calculations from LME data. Series show annual proportionate growth of median firm real wages.

Figure 3. Provincial Data: Secondary Industry Labor Productivity Growth



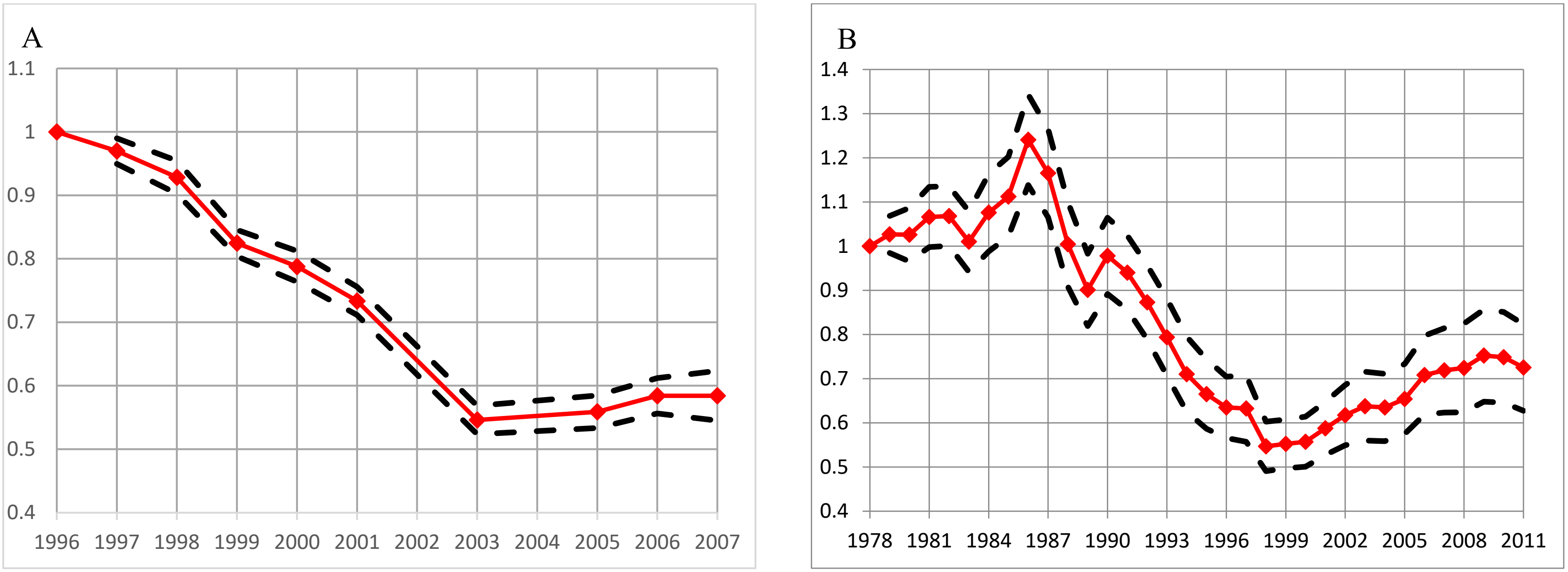
Source: Authors' calculations from China Statistical Yearbook

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



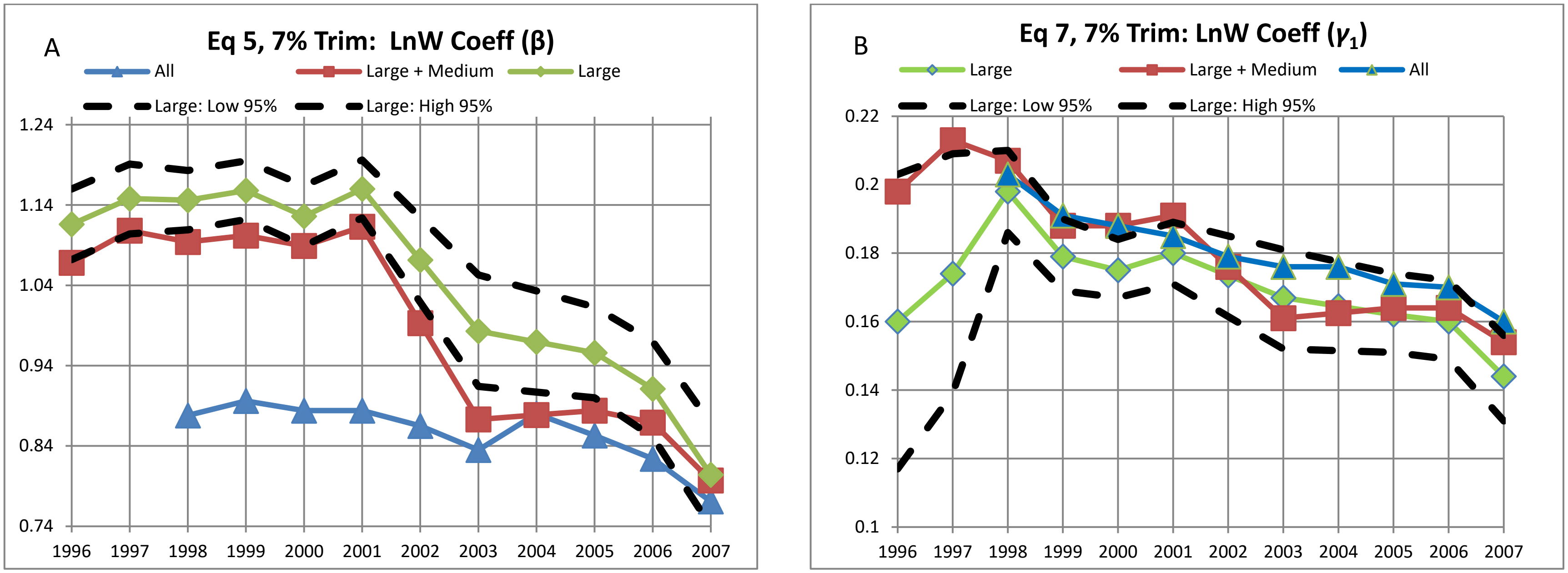
Source: Authors' calculations from LME data.

Figure 5. Estimates of Equation (4a) based on $(1-\theta_t)/(1-\theta_0)$ and 95% Confidence Intervals



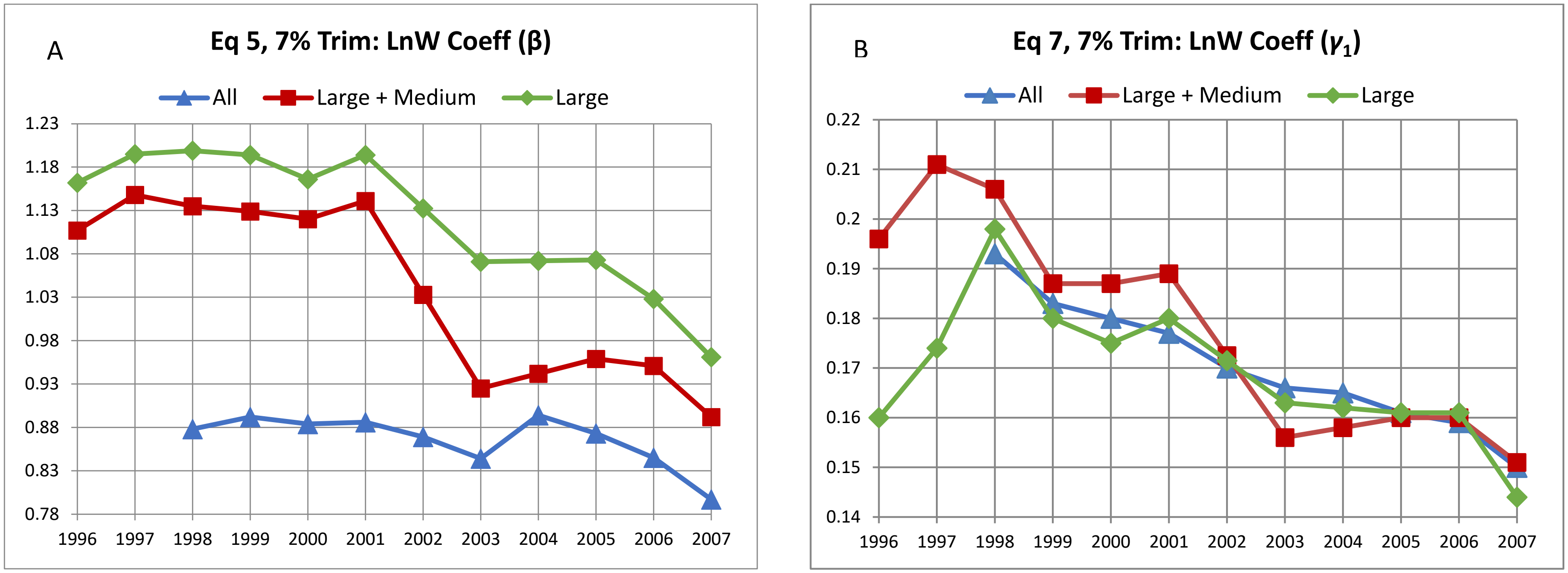
Notes: (1) Panel A focuses on the subsample of the Large enterprises; (2) Panel B focuses on provincial data.

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



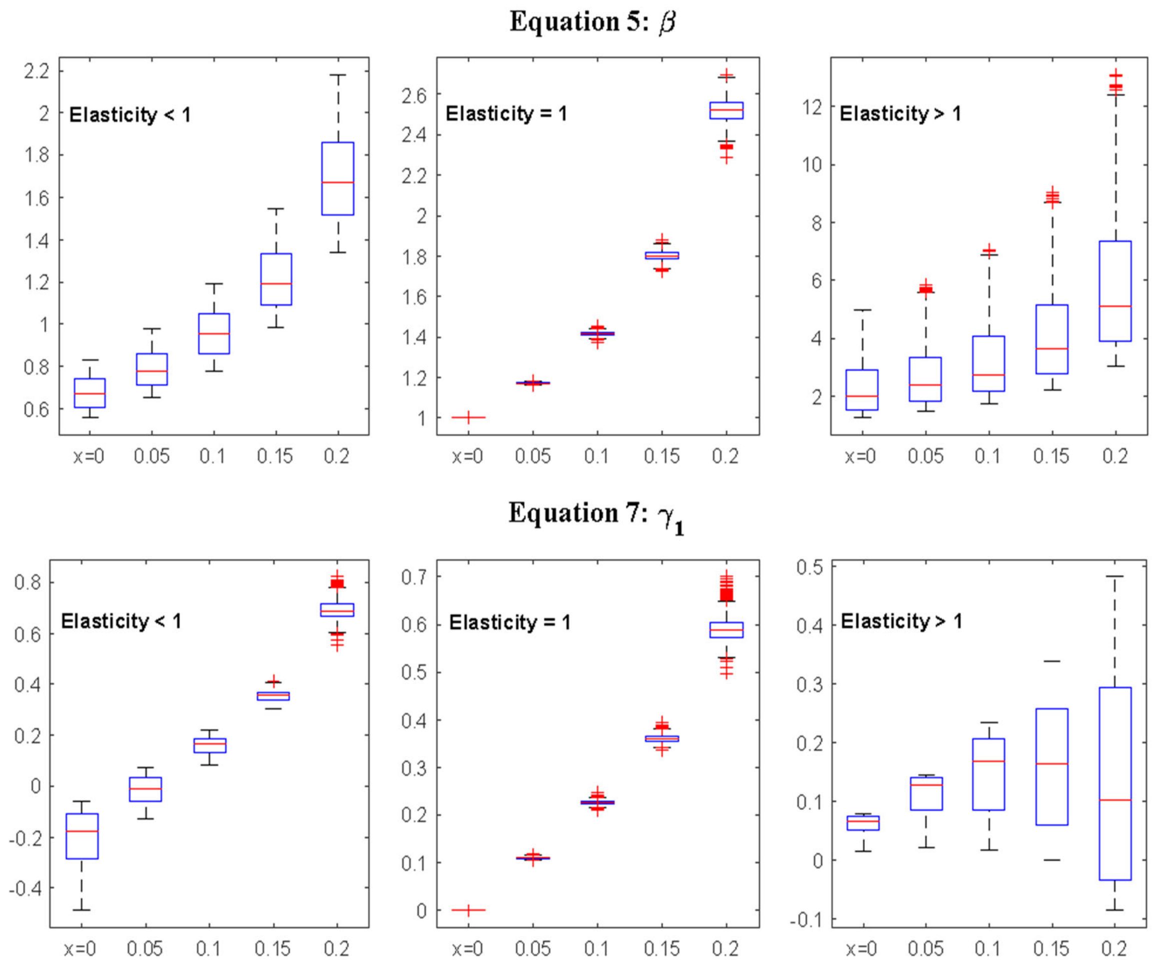
Notes: Authors' calculations from LME data.
Years 2002 and 2004 for Large and Large + Medium samples and their confidence intervals are interpolated.

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



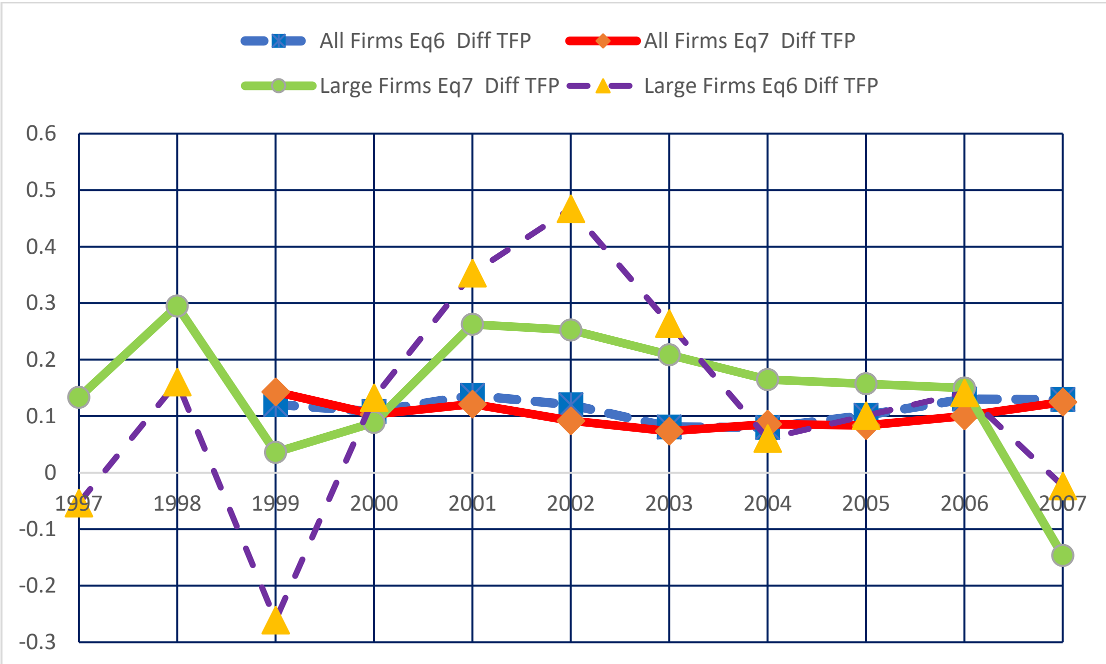
Notes: Authors' calculations from LME data.
Years 2002 and 2004 for Large and Large + Medium samples and their confidence intervals are interpolated.

Figure 8 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.

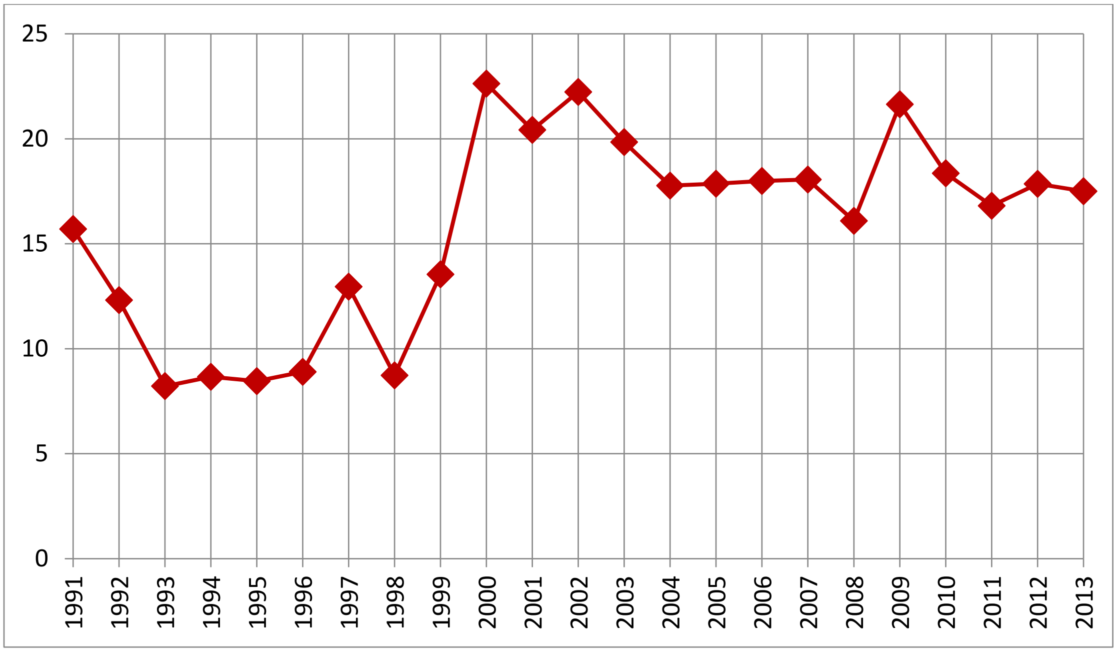
Figure 9 TFP Growth



Notes: Authors' calculations from LME data. Log TFP is based on coefficients of year dummy variables estimated from equations (6) $\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \theta \ln\left(\frac{\overline{K}}{L}\right)_{it} + \varepsilon_{it}$ and (7)

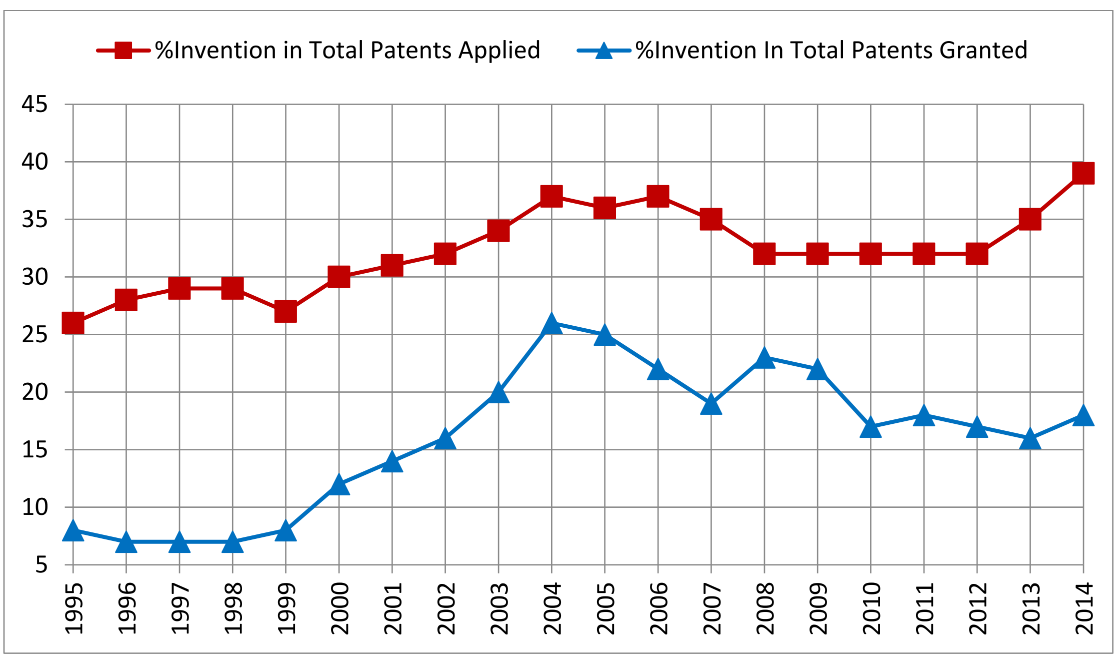
$\ln\left(\frac{Y}{L}\right)_{it} = B_{it} + \gamma_0 \ln\left(\frac{\overline{K}}{L}\right)_{it} + \gamma_1 f(W_{it}) \ln\left(\frac{\overline{K}}{L}\right)_{it} + \gamma_2 f(\overline{K}_{it}) \ln\left(\frac{\overline{K}}{L}\right)_{it} + \varepsilon_{it}$. Years 2002 and 2004 for Large-Firm samples are interpolated.

Figure 10 Annual Growth of R&D Stock (%)



Source: Authors' calculations.

Figure 11 Percentage of Invention in Total Patents Applied for & Granted



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

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 Labor Force (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 Estimation Results of Equation 5: Provincial Secondary Industry Data

	(1)		(2)	
	1st Stage	2nd Stage	1st Stage	2nd Stage
VARIABLES	Log Wage (t-1)	Log Y/L	Log Wage (t-1)	Log Y/L
Log Wage (t-1)		1.648** (0.653)		1.589*** (0.609)
Log R&D Stock (t-1)			0.027 (0.064)	-0.043 (0.182)
Log FDI Stock (t-1)			0.025 (0.117)	0.043 (0.041)
Log Primary Emp. (t-10)	-0.211** (0.011)		-0.226*** (0.081)	
Log Secondary K Stock (t-1)			0.064 (0.068)	-0.138 (0.113)
Observations	604	604	604	604
Years	1991 - 2011		1991 - 2011	
Test Beta = 1: p-value		0.321		0.334
Weak ID Stat	6.468		7.826	

Notes:

- 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 a time trend (current year – 1978).
- Regions: Coast = Fujian, Tianjin, Shandong, Hebei, Beijing, Zhejiang, Hainan, Shanghai, Jiangsu, and Guangdong; Northeast = Jilin, Heilongjiang, and Liaoning; Central = Hubei, Chongqing, Sichuan, Guizhou, Jiangxi, Hunan, Inner Mongolia, Anhui, Guangxi, Yunnan, Henan, and Shanxi; Far West = Gansu, Qinghai, Tibet, Xinjiang, and Ningxia.
- R&D stock are not available for Tibet; FDI stock data are not available for Chongqing or for Tibet in 1992.
- The standard errors are clustered at the province level. *, **, *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

Table 4 Estimation Results of Equation 7: Provincial Secondary Industry Data

	(1)		(2)	
	1st Stage	2nd Stage	1st Stage	2nd Stage
VARIABLES	Log Wage (t-1) x Log K/L (t-1)	Log Y/L	Log Wage (t-1) x Log K/L (t-1)	Log Y/L
Log Wage (t-1) x Log K/L (t-1)		0.136*** (0.042)		0.205*** (0.059)
Log Secondary K Stock (t-1) x Log K/L (t-1)	0.309*** (0.077)	-0.091*** (0.022)		
Log K/L (t-1)	9.086*** (0.571)	-0.059 (0.279)	11.495*** (0.296)	-1.571*** (0.515)
Log Primary Emp. (t-10) x Log K/L (t-1)	-0.437*** (0.000)		-0.354*** (0.354)	
Observations	642	642	642	642
Years	1991 - 2011		1991 - 2011	
Weak ID Stat	118.7		58.55	

Notes: The standard errors are clustered at the province level. *, **, *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

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 Predictions of β and γ_1

Assumed Elasticity of Substitution	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 $\gamma_1 > 0$