Technical Progress and Induced Innovation in China: A Variable Profit Function Approach

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Abstract

We propose a new methodology to estimate empirically the input price-induced technical change and total factor productivity (TFP) growth in China. Our primary goal is to test Hicks' induced innovation hypothesis by examining whether technical change in China has been induced by sharp increase in input prices that have accompanied its rapid economic growth. Utilizing the idea of a firm's two-stage optimization problem, we develop a new parametric form of the variable profit function wherein the derived input demand and output supply functions can be easily constrained to be regular, and the functional structure is parsimonious in the number of parameters. Applying this methodology to Chinese time series data for 1986–2015, we find that not only is wage-induced innovation significant and quantitatively important, but also that it substantially buffers a long-term decline in TFP growth that would otherwise be quite substantial. We conclude that China's economic growth is predominantly driven by wage-induced innovation along with massive injection of heavily subsidized physical inputs in public works and huge investment in industrial sectors.

Key Words: Induced Innovation; Total Factor Productivity; Variable Profit Functions; China.

JEL Classification: D22, D24, O30, O53.

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1. Introduction

Empirical estimates of total factor productivity (hereafter TFP) as an indicator of overall technical progress are of great interest to both analysts and policy makers. Accurate measurement of TFP can help them better understand the effects of major initiatives such as tax and tariff policies and the impacts of changes in available resources (raw materials, produced factors, and labor) on output growth. The challenge put forward by Abramovitz (1956, "…the …importance…of productivity increase …may be taken as some sort of measure of our ignorance about the causes of economic growth…") has stimulated an immense body of research focusing on the role, nature, and causes of innovation and technology progress. We mention two subsequent pioneering often-quoted papers that emphasize the role of TFP growth—the seminal work of Solow (1957) and that of Mankiw, Weil, and Romer (1992). Based on this body of thought, in some countries TFP growth rate is adopted as a target in national development plans.

In view of the phenomenal growth rates and persistent structural changes in China since 1978, there has been extensive interest in measuring the level and growth of TFP in China. Recent studies include Wu (2000, 2003), Zhao and Zhang (2010), Chen et al. (2011), Hong and Sun (2011), Cao and Birchenall (2013) and Chen et al. (2018). In general, these studies use time series or panel data from 1980 through the 2010s, but none of them address whether technical change is induced by changes in wage rates and other input prices accompanied by rapid economic growth in China.

Input price-induced innovation (hereafter induced innovation) is defined in Hicks (1932, pp. 124-125), where he wrote, "*a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind—directed to* *economizing the use of a factor which has become relatively expensive.*" As explained by Shumway et al. (2015), it is an important hypothesis with useful policy relevance. If this hypothesis is valid, then distortionary taxes or subsidies aimed at synchronizing market and social input prices would affect not only contemporary input use but also future input use through research investment decisions to create factor-saving innovation that aligns public cost with private cost (Nordhaus, 2002; Shumway et al., 2015). In recent years, this issue has received increasing attention and been tested empirically for several advanced economies, generally in narrowly defined industry categories (see, e.g., Yuhn, 1991; Celikkol and Stefanou, 1999; Okini, 2000; Esposti and Pierani, 2008).

Ours constitutes the first attempt to bridge the gap between the pure theory of induced innovation and its empirical implementation for China. We propose a new modeling procedure, which enables the identification of induced innovation by means of a variable profit function framework. The main advantage of using the variable profit function over the more conventional cost-function approach is that it is more general than using the cost function since a firm's profit maximizing behavior always implies cost minimization, but not vice versa. Additionally, the variable profit function allows the levels of outputs and inputs to be adjusted endogenously and thus adapted to changes in output/input prices and technology. These advantages avoid inconsistencies in the econometric estimates due to simultaneous equation problems, and they overcome a major limitation of the cost function that output levels are not affected by factor price changes and thus cannot address the possible indirect effect of these changes (via output levels) on factor demand.[1]

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[1] See Lopez (1984, p. 358) and Karagiannis and Mergos (2000, p. 32).

Applying the proposed methodology to the Chinese data for 1986-2015, we identify two important sources of TFP growth using the parameter estimates of a variable profit function: (i) Type I technical progress, which include, for example, productivity growth resulting from exogenous technological progression and resource allocation shocks; and (ii) productivity growth resulting from induced innovation, defined as Type II technical progress.

The Chinese economy provides a rich source of data that could be used to test the induced innovation hypothesis and to identify the sources of productivity growth. In particular, China overtook Japan as the world's second-largest economy in 2010, and its opening up to the world economy when accessing the WTO in 2001 has often been applauded as a paradigm for economic development. The impressive economic growth together with sharp increase in real wage rates make it an appealing subject to investigate empirically the role that induced innovation has played in China's technical progress. We firmly believe that these findings could provide useful insight into the understanding of China's spectacular growth over the last three decades, and that they shed light on the issue of redistribution of income caused by economic growth.

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework and the derivation of the empirical models underlying our work from static duality theory. Empirical implementation of the model is discussed in Section 3. Section 4 presents a brief discussion of the data set and the estimation method. Interpretation of empirical findings is provided in Section 5. Section 6 concludes.

2. Theoretical Framework

We develop the firm's optimization problem as a two-stage procedure whereby: (i) in the first stage, the firm chooses variable inputs $\mathbf{x}_t$ to maximize its variable profit; and (ii) in the second stage, the optimal technology v_t is determined so as to maximize variable profit net of the overhead cost of adopting new technology. Suppose that the firm's technology is characterized by a production function:

$$y_t = F\left(\mathbf{x}_t, \mathbf{z}_t, v_t\right), \tag{1}$$

where y_t is the quantity of a single output to be produced at time t, which is twice continuously differentiable, increasing and concave in $\left(\mathbf{x}_t, \mathbf{z}_t, v_t\right)$, $\mathbf{x}_t$ is the N1 x 1 vector of variable inputs, $\mathbf{z}_t$ is the N2 x 1 vector of fixed inputs, and v_t measures the state of technology at time t.

Denoting output price as p_t and variable input prices as $\mathbf{w}_t = \{w_{it}\}$, we write the firm's first stage problem as:

$$\Pi\left(p_t, \mathbf{w}_t, \mathbf{z}_t, v_t\right) = \text{Max}_{\mathbf{x}_t}\, p_t \cdot \mathrm{F}\left(\mathbf{x}_t, \mathbf{z}_t, v_t\right) - \mathbf{w}_t^{'}\mathbf{x}_t, \tag{2}$$

which is the firm's variable profit function. Based on its definition (2), the variable profit function will inherit the regularity conditions **RΠ**:

RΠ1: Π is positive;

RΠ2: Π is twice continuously differentiable;

RΠ3: Π is increasing in $\left(p_t, \mathbf{z}_t, v_t\right)$;

RΠ4: Π is decreasing in $\mathbf{w}_t$;

RΠ5: Π is homogeneous of degree one (hereafter HD1) in $\left(p_t, \mathbf{w}_t\right)$;

RΠ6: Π is convex in $\left(p_t,\ \mathbf{w}_\mathrm{t}\right)$; and

RΠ7: Π is concave in $\mathbf{z}_\mathrm{t}$.

The solutions yield:

$$x_{it} = \mathrm{X}_\mathrm{i}^{\mathrm{HL}}\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ v_t\right), \text{ and} \tag{3}$$

$$y_t = \mathrm{Y}^{\mathrm{HL}}\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ v_t\right), \tag{4}$$

which are the Hotelling-Lau (hereafter HL) variable input demand $\left(\mathrm{X}_\mathrm{i}^{\mathrm{HL}}\right)$ and output supply $\left(\mathrm{Y}^{\mathrm{HL}}\right)$ functions, respectively. This system of equations is related to the HL variable profit function via Hotelling's lemma:

$$\mathrm{X}_\mathrm{i}^{\mathrm{HL}}\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ v_t\right) = -\frac{\partial \Pi}{\partial w_{it}}, \text{ and} \tag{5}$$

$$\mathrm{Y}^{\mathrm{HL}}\left(p_t, \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ v_t\right) = \frac{\partial \Pi}{\partial p_t}.$$

Given the HL variable profit function, the firm's second-stage problem is to choose the optimal level of v_t to maximize the level of variable profit net of the overhead cost of adopting new technology:

$$\Pi^{\mathrm{V}}\left(p_t,\ \mathbf{w}_t,\ \mathbf{z}_t,\ v_t\right) = \mathrm{Max}_{\ v_t} \Pi\left(p_t,\ \mathbf{w}_t,\ \mathbf{z}_t,\ v_t\right) - \mathrm{C}\left(v_t,\ \overline{v}_{t-1}\right), \tag{6}$$

where $\overline{v}_{t-1}$ is the level of technology chosen in the previous period. The function $\mathrm{C}\left(v_t,\ \overline{v}_{t-1}\right)$, defining the overhead cost of adopting new technology, is assumed to be positive, increasing and convex in $\left(v_t, \overline{v}_{t-1}\right)$. Maximizing (6) and treating $\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \overline{v}_{t-1}\right)$ as conditioning variables, we write the firm's optimal value of v_t as a function of $\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \overline{v}_{t-1}\right)$:

$$v_t = \mathrm{V}^*\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \overline{v}_{t-1}\right). \tag{7}$$

Substituting (7) into (2), (3) and (4) yields the HL variable profit, input demand and output supply functions corresponding to the second-stage problem of choosing new technology; i.e.,

$$\Pi\left[p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \mathrm{V}^*\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \overline{v}_{t-1}\right)\right] = \Pi^*\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \overline{v}_{t-1}\right), \tag{8}$$

$$x_{it} = \mathrm{X}_\mathrm{i}^\mathrm{HL}\left[p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \mathrm{V}^*\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \overline{v}_{t-1}\right)\right] = \mathrm{X}_\mathrm{i}^*\left(p_t,\ \mathbf{w}_\mathrm{t},\ \mathbf{z}_\mathrm{t},\ \overline{v}_{t-1}\right), \text{ and} \tag{9}$$

$$y_t = \mathrm{Y}^\mathrm{HL}\left[\mathrm{p}_t,\ \mathbf{w}_t,\ \mathbf{z}_t,\ \mathrm{V}^*\left(p_t,\ \mathbf{w}_t,\ \mathbf{z}_t,\ \overline{v}_{t-1}\right)\right] = \mathrm{Y}^*\left(p_t,\ \mathbf{w}_t,\ \mathbf{z}_t,\ \overline{v}_{t-1}\right), \tag{10}$$

where the impacts of disembodied technical change and induced innovation on production technology are captured by the optimizer V^*. Provided that V^* solves the second-stage optimization problem, it inherits the following regularity conditions **RV**:

RV1: V^* is positive;

RV2: V^* is twice continuously differentiable;

RV3: V^* is increasing in $\left(p_t,\ \mathbf{z}_t,\ \overline{v}_{t-1}\right)$;

RV4: V^* is decreasing in $\mathbf{w}_t$;

RV5: V^* is HD0 in $\left(p_t,\ \mathbf{w}_t\right)$;

RV6: V^* is convex in $\left(p_t,\ \mathbf{w}_t\right)$; and

RV7: V^* is concave in $\mathbf{z}_t$.

Empirical investigation of variable profit functions usually proceeds by choosing a flexible functional form to represent the level of profit, using Hotelling's lemma to derive the implied input demand and output supply functions, and then estimating these functions. Based on this approach, the incorporation of disembodied technical change and induced innovation depends merely on the exact functional form of the chosen variable profit function and thus may rule out complicated interactions of technical changes with input and output prices. Moreover, the usual approach can eliminate many potential models that are attractive in their simplicity and regularity. More importantly, traditional flexible functional forms do not guarantee global regularity, implying that the estimated variable profit function may fail to satisfy the monotonicity and curvature conditions, and therefore it may be unsuitable for use in applied general equilibrium modelling and in policy analyses.

To deal with the limitations of conventional estimation of variable profit functions, in the next section we introduce an approach that is in principle free from the above problems and is readily applicable to empirical estimation.

3. Empirical Implementation of the Variable Profit Function

In this section, we illustrate the specification on which our empirical analysis is based. The general functional structure of the variable profit function (Π^*) is based on Cooper et al.'s (2001) Modified Gorman-Polar form (hereafter MGPF). This choice is motivated primarily by the simplicity of its functional structure as well as the ease of imposing and maintaining regularity conditions and by the feature that the number of parameters does not increase rapidly with the number of inputs and outputs under consideration.

We assume one type of fixed input (N2 = 1) and write the MGPF variable profit function as:

$$\Pi\left(p_t,\ \mathbf{w}_t,\ z_t,\ V^*\right) = \left\{\frac{p_t^{1+\eta}}{\left[\mathrm{W3}\left(\mathbf{w}_t\right)\right]^{\eta}}\right\}\left\{\log\left[\frac{z_t \cdot \mathrm{V}^* \cdot p_t}{\mathrm{W1}\left(\mathbf{w}_t\right)}\right]-1\right\} - \frac{\mathrm{W2}\left(\mathbf{w}_t\right)}{z_t^{\phi}}, \qquad (11)$$

where η and ϕ are parameters, and $W\ell(\mathbf{w}_t)$, ℓ =1, 2 and 3, are input price indexes satisfying the regularity conditions **RW**:

RW1: $W\ell$ is positive;

RW2: $W\ell$ is twice continuously differentiable;

RW3: $W\ell$ increasing in $\mathbf{w}_t$;

RW4: $W\ell$ is HD1 in $\mathbf{w}_t$; and

RW5: $W\ell$ is concave in $\mathbf{w}_t$.

Using the intuition stemming from Cooper and McLaren's (1996) General Exponential form and their ideas about effective global regularity, we choose the $W\ell$ as follows:

$$W1(\mathbf{w}_t) = \prod_{i=1} w_{it}^{\alpha_i}, \ \sum_i \alpha_i = 1, \ W2(\mathbf{w}_t) = \sum_{i=1} \gamma_i w_{it}, \text{ and } W3(\mathbf{w}_t) = \sum_{i=1} \left(\varsigma_i w_{it}^{\rho}\right)^{1/\rho}, \ \sum_{i=1} \varsigma_i = 1,$$

where α_i, γ_i, ζ_i and ρ are parameters. Furthermore, V^*, representing the solution of the second stage optimization problem, is given by:

$$V^*(\tilde{\mathbf{w}}_{t\text{-}1}, t) = e^{\left[\delta + \tau \cdot t + \sum_j \lambda_j \log\left(\tilde{w}_{jt\text{-}1}\right)\right]}, \tag{12}$$

where δ, τ, and λ_j are parameters, t is the index of time, and $\tilde{\mathbf{w}}_{t\text{-}1}$ is the N1 x 1 vector of long-run variable input prices lagged by one period. As shown in (12), the variable profit function depends indirectly on $(\tilde{\mathbf{w}}_{t\text{-}1}, t)$ through the V^* function in its technological state argument v_t.[2]

[2] To be consistent with the second stage problem (6), we realize that $\left(p_t, \mathbf{w}_t, z_t\right)$ should be the conditioning variables of the optimizer V^*. Preliminary results however indicate the incorporation of these variables is

Substituting (12) into (11), we obtain:

$$\Pi^*\left(p_t, \mathbf{w}_t, z_t; \tilde{\mathbf{w}}_{t-1}, t\right) = \Pi\left[p_t, \mathbf{w}_t, z_t; V^*\left(\tilde{\mathbf{w}}_{t-1}, t\right)\right]$$

$$= \left\{\frac{p_t^{1+\eta}}{\left[W3\left(\mathbf{w}_t\right)^{\eta}\right]}\right\}\left\{\log\left[\frac{z_t \cdot V^*\left(\tilde{\mathbf{w}}_{t-1}, t\right)\cdot p_t}{W1\left(\mathbf{w}_t\right)}\right]-1\right\} - \frac{W2\left(\mathbf{w}_t\right)}{z_t^{\phi}}, \qquad (13)$$

which is the general form of the MGPF profit function. Following Peeters and Surry (2000), technical change in (13) is represented by two separate terms: (i) the time index t (referred to as the disembodied or Type I technical change) which is unrelated to changes in lagged input prices $\tilde{\mathbf{w}}_{t-1}$; and (ii) the lagged input price vector $\tilde{\mathbf{w}}_{t-1}$ which reflects the input price-induced (referred to as Type II) technical change.

Via Hotelling's lemma, logarithmic differentiation of (13) with respect to output price and input prices respectively produces the output supply and input demand functions in profit share form:

$$S_{Y_t^*}\left(p_t, \mathbf{w}_t, z_t; \tilde{\mathbf{w}}_{t-1}, t\right) = \frac{p_t Y_t^*}{\Pi^*} = \frac{\partial \log\left(\Pi^*\right)}{\partial \log\left(p_t\right)} = \frac{p_t^{1+\eta}\left[\left(1+\eta\right)R_t + 1\right]/W3^{\eta}}{p_t^{1+\eta}\cdot R_t/W3^{\eta} - W2/z_t^{\phi}}, \text{ and } (14)$$

$$S_{X_{it}^*}\left(p_t, \mathbf{w}_t, z_t; \tilde{\mathbf{w}}_{t-1}, t\right) = \frac{w_{it}X_{it}^*}{\Pi^*} = \frac{-\partial \log\left(\Pi^*\right)}{\partial \log\left(w_{it}\right)},$$

$$= \frac{\dfrac{\gamma_i w_{it}}{z_t^{\phi}} + p_t^{1+\eta}\left[\alpha_i + \eta E_{W3w_{it}}\cdot R_t\right]\Big/W3^{\eta}}{p_t^{1+\eta}\cdot R_t/W3^{\eta} - W2/z_t^{\phi}}, \qquad (15)$$

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statistically insignificant (based on the Wald test results). Therefore, we make the theoretical model more empirically operational by simplifying (7) as $V^*\left(\tilde{\mathbf{w}}_{t-1}, t\right)$.

where $\mathrm{R_t} = \log\left[\frac{z_t \cdot \mathrm{V}^* \cdot p_t}{\mathrm{W1}}\right] - 1$ and $\mathrm{E_{W3w_{it}}} = \frac{\partial \log(\mathrm{W3})}{\partial \log(w_{it})} = \frac{\varsigma_i w_{it}^{\rho}}{\sum_j \varsigma_j w_{jt}^{\rho}}$. Given the specifications of $\mathrm{W}\ell$ and V^*, the sufficient conditions to ensure (13) to be a regular variable profit function over the regions ($z_t \cdot \mathrm{V}^* \cdot p_t > \mathrm{W1}$ and $x_i \geq \gamma_i\ \forall$ i) are:

$$0 \leq \eta,\ \phi,\ \alpha_i,\ \varsigma_i \leq 1,\ \ \rho \leq 1 \text{ and } \gamma_i \geq 0. \tag{16}$$

Differentiation of the variable profit function (Π^*) with respect to the time index t (or lagged input prices $\tilde{w}_{\text{jt-1}}$) yields:

$$\frac{\partial \Pi^*}{\partial t} = \left[\frac{p_{\mathrm{t}}^{1+\eta}}{\mathrm{W3}^{\eta}}\right]\tau \text{ or} \tag{17}$$

$$\frac{\partial \Pi^*}{\partial \tilde{w}_{\text{jt-1}}} = \left[\frac{p_{\mathrm{t}}^{1+\eta}}{\mathrm{W3}^{\eta}}\right]\frac{\lambda_{\mathrm{j}}}{\tilde{w}_{\text{jt-1}}}. \tag{18}$$

In addition, partial differentiation of the input demand share functions with respect to the lagged input prices gives:

$$\frac{\partial \mathrm{S}_{\mathrm{X}_{\mathrm{it}}^*}}{\partial \log\left(\tilde{w}_{jt-1}\right)} = \frac{\frac{p_t^{1+\eta}}{\mathrm{W3}^{\eta}}\left(\eta \cdot \mathrm{E_{W3w_{it}}} - S_{\mathrm{X}_{\mathrm{it}}^*}\right)\lambda_{\mathrm{j}}}{\Pi^*}. \tag{19}$$

Clearly from (17) [or (18) and (19)], the significance of Type I (or II) technical change corresponds to the parameter restriction(s) $\tau = 0$ (or $\lambda_{\mathrm{j}} = 0\ \forall$ j). Given (17), the rate of technical progress $\left(\mathrm{RTP}_t\right)$ is given by:

$$\mathrm{RTP_t} = \frac{\partial \Pi^* / \partial t}{p_t \cdot \left(\partial \Pi^* / \partial p_t\right)} = \frac{\tau}{(1+\eta)\mathrm{R}_t + 1}.^{3} \tag{20}$$

3 See Ray and Segerson (1990, p.44).

To describe existing substitution possibilities, we define $E_{M^*_{i't} ex_{j't}}$ as a set of HL elasticities. Specifically:

$$E_{M^*_{i't} ex_{j't}} = \frac{\partial \log(M^*_{i't})}{\partial \log(ex_{j't})}, \tag{21}$$

where $\mathbf{M}^*_t = \{Y^*_t, X^*_{1t}, ..., X^*_{Nt}\}$ and $\mathbf{ex}_t = \{p_t, w_{1t}, ..., w_{Nt}, z_t, \tilde{w}_{1t-1}, ..., \tilde{w}_{Nt-1}, t\}$. For instance, $E_{X^*_{it}\tilde{w}_{jt}} = \frac{\partial \log(X^*_{it})}{\partial \log(\tilde{w}_{jt-1})}$, is the HL lagged price elasticity of the ith input with respect to the jth lagged prices; $E_{X^*_{it}e^t} = \frac{\partial \log(X^*_{it})}{\partial \log(e^t)} = \frac{\partial \log(X^*_{it})}{\partial t}$, is the HL time semi-elasticity of the ith input. Parametric specifications of these elasticity equations are presented in Table 1.

It is tempting to consider the HL lagged price elasticities $(E_{X^*_{it}\tilde{w}_{jt-1}})$ as indicators of induced innovation. This interpretation however is not strictly precise since all the HL elasticities are constructed under the assumption that output price rather than the level of output is held constant. Based on the definition of induced innovation in Hicks (1932), the pure substitution effects of lagged price changes cannot be truly represented via the HL lagged price elasticities. A legitimate way to measure the effects of induced innovation as used in the literature is to derive the Hicksian lagged price $(E_{X^H_{it}\tilde{w}_{jt-1}})$,[4] which may require an empirically calibrated variable cost function rather than the corresponding variable profit function.

Although the analytical form of the cost function dual to MGPF is unavailable, we

[4] See Peeters and Surry (2000, p.61) and Esposti and Pierani (2008, pp. 14-15).

can obtain the Hicksian elasticity equations via the following identity:

$$\mathrm{X}_{\mathrm{it}}^{*}\left(p_{\mathrm{t}},\ \mathbf{w}_{\mathrm{t}},\ z_{t};\ \tilde{\mathbf{w}}_{\mathrm{t-1}},t\right)=\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}\left[\mathrm{Y}_{t}^{*}\left(p_{t},\ \mathbf{w}_{\mathrm{t}},\ z_{t};\ \tilde{\mathbf{w}}_{\mathrm{t-1}},t\right),\ \mathbf{w}_{\mathrm{t}},z_{t};\ \tilde{\mathbf{w}}_{\mathrm{t-1}},t\right], \tag{22}$$

where $\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}$ is the ith Hicksian (or cost minimizing) input demand function, and the superscript H indicates that these functions depend on the level of output.[5] In particular, the Hicksian lagged price elasticities $\left[\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}\tilde{\mathrm{w}}_{\mathrm{jt-1}}}=\dfrac{\partial\log\left(\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}\right)}{\partial\log\left(\tilde{w}_{jt-1}\right)}\right]$, recognized as the standard measures of induced innovation effects may be derived via the partial derivative of (22) with respect to the lagged input prices $\tilde{w}_{jt-1}$; i.e.,

$$\frac{\partial\mathrm{X}_{\mathrm{it}}^{*}}{\partial\tilde{w}_{jt-1}}=\frac{\partial\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}}{\partial y_{t}}\frac{\partial\mathrm{Y}_{\mathrm{t}}^{*}}{\partial\tilde{w}_{jt-1}}+\frac{\partial\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}}{\partial\tilde{w}_{jt-1}}.$$

This relationship can be rewritten in terms of elasticity equations:

$$\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}\tilde{\mathrm{w}}_{\mathrm{jt-1}}}=\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{*}\tilde{\mathrm{w}}_{\mathrm{jt-1}}}-\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}\mathrm{y}_{\mathrm{t}}}\cdot\mathrm{E}_{\mathrm{Y}_{\mathrm{t}}^{*}\hat{\mathrm{w}}_{\mathrm{jt-1}}}=\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{*}\tilde{\mathrm{w}}_{\mathrm{jt-1}}}-\frac{\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{*}\mathrm{p}_{\mathrm{t}}}}{\mathrm{E}_{\mathrm{Y}_{\mathrm{t}}^{*}\mathrm{p}_{\mathrm{t}}}}\cdot\mathrm{E}_{\mathrm{Y}_{\mathrm{t}}^{*}\tilde{\mathrm{w}}_{\mathrm{jt-1}}}, \tag{23}$$

where $\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}\mathrm{y}_{\mathrm{t}}}=\dfrac{\partial\log\left(\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}\right)}{\partial\log\left(y_{t}\right)}=\dfrac{\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{*}\mathrm{p}_{\mathrm{t}}}}{\mathrm{E}_{\mathrm{Y}_{\mathrm{t}}^{*}\mathrm{p}_{\mathrm{t}}}}=\dfrac{\partial\log\left(\mathrm{X}_{\mathrm{it}}^{*}\right)/\partial\log\left(p_{t}\right)}{\partial\log\left(\mathrm{Y}_{\mathrm{t}}^{*}\right)/\partial\log\left(p_{t}\right)}$ represents the Hicksian scale elasticity of the ith input, and $\mathrm{E}_{\mathrm{X}_{\mathrm{it}}^{*}\mathrm{p}_{\mathrm{t}}}$ and $\mathrm{E}_{\mathrm{Y}_{\mathrm{t}}^{*}\mathrm{p}_{\mathrm{t}}}$ are defined in Table 1. Once the HL lagged price elasticities are estimated, the Hicksian lagged price elasticities can be computed via (23).

Two nested special cases of the MGPF profit function (13) are of interest:

<u>Case 1</u>: $\phi = \eta = 0$. Then, (13) reduces to the Gorman Polar Form (hereafter GPF), a generalization of the linear expenditure system in the context of consumer demands.

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[5] See Chambers (1988, p.132).

Case 2: $\phi = 0$. In this case, Π is of the form: $\Pi^* = \left(\frac{p_t^{1+\eta}}{W3^\eta}\right)\left[\log\left(\frac{z_t \cdot V^* \cdot p_t}{W1}\right) - 1\right]$ - W2

which is referred to as the Extended GPF (hereafter EGPF).

4. Data and Estimation Method

The MGPF form is used to estimate a variable profit function for China with annual data covering the period 1986-2015. In the model, we consider one single output (y_t), one fixed input, capital (z_t), and four variable inputs: labor (x_{1t}), oil (x_{2t}), coal (x_{3t}) and imports (x_{4t}).[6]

Definitions and Sources of Data: We obtain nominal GDP and its deflator from the 2017 China Statistical Yearbook. Type I technical change is approximated by a single linear trend variable (*t*) with unit annual increments and normalized to one for 1987. Holz and Sun (2018) provide the data of capital services, and we obtain the data of crude oil and coal consumption from the National Bureau of Statistics of China (2010, 2019);[7] the price of oil (or coal) is found in the 2016 Daqing Statistical Yearbook [or China Prices Press (1998) and Wu et al. (2016)].

Data on total labor cost and wage rate are found in the China Compendium of Statistics and in various years of China Statistical Yearbook. Labor unit cost (price of labor) is calculated using the labor income component of GDP divided by total labor force. The quantity index of China's total imports is obtained from publications of the General

[6] Following Kohli (1978 and 1993), we treat imports as an intermediate input of production, which is appropriate in the case of China. As indicated by Xu and Mao (2018), the share of imports that consist of intermediate inputs has increased from 67.6% to 78.6 % during 1995-2013. In addition, retail and domestic handling are still needed for most finished imported goods.

[7] Data on coal and oil consumption are net of that used for non-production purposes.

Administration of Customs of China (1993 and 2008) and in the CEIC China premium database (2019); data to construct its price index are available in various years of the China Statistical Yearbook.

We calculate the price series for the variable inputs ($\tilde{\mathbf{w}}_{t\text{-}1}$) from the sources cited above and generate three-year moving averages, e.g., $\tilde{\mathbf{w}}_{t\text{-}1} = \dfrac{\mathbf{w}_{t\text{-}3} + \mathbf{w}_{t\text{-}2} + \mathbf{w}_{t\text{-}1}}{3}$. The set of variable input and output prices as well as fixed input quantity used in our estimations are normalized by dividing through by their respective geometric means.

Stochastic Specification of the Share Equations: Assuming that the HL variable profit share equations of output and inputs (14) and (15) are exact, except for errors in optimization, we add to this system of equations a vector of error terms $\mathbf{u}_t$ assumed to be identically distributed as a normal random vector with mean zero and covariance matrix $\mathbf{\Omega}$. Letting $\mathbf{s}_t$ denote the column vector of the observations of input and output shares at time t, the system of five output/input share equations can be more compactly written as:

$$\mathbf{s}_t = \mathbf{S}\left(\mathbf{ex}_t;\ \boldsymbol{\beta}\right) + \mathbf{u}_t, \tag{24}$$

where $\mathbf{S}$ is the vector of the deterministic component of the supply/demand share equations, $\mathbf{ex}_t$ is the vector of all exogenous variables, and $\boldsymbol{\beta}$ is a vector of parameters. Since the output and input shares sum to one, the covariance matrix of $\mathbf{u}_t$ is singular, and hence so is its covariance matrix $\mathbf{\Omega}$. Accordingly, one equation in the system (24) must be omitted for estimation purpose, but the parameter estimates are independent of which equation is excluded.

To accommodate evidence of significant positive serial correlation revealed in initial estimation, we introduce the first-order autoregressive scheme based on an order N parameterization of the autocovariance matrix using the full information maximum likelihood algorithm of Moschini and Moro (1994).[8]

In our theoretical model, we treat capital input and output/input prices as given. Except for capital input, this treatment may be inappropriate in a statistical sense since China, due to its size, is unlikely to face perfectly elastic export demand and import supply schedules. Furthermore, domestic price of output (p_t) may be endogenous since it is determined by interaction of domestic demand (which is not modeled here) and supply.[9] The potential endogeneity of the output and import prices suggests that we need to use an appropriate estimation method. We thus employ the iterative three stage least square (3SLS) technique. The following set of instruments were considered: the squared time trend, and the first-order lags of labor, oil and coal prices.

5. Empirical Results

Analysis of Measures of Fit: All estimation was carried out using the 3SLS procedure in the TSP version 5.1 computer package, which is well-suited for estimation of equation systems with complex cross-equation constraints; it also allows for heteroscedasticity of an unknown form in the computation of the variance-covariance matrix. The MGPF and its nested specifications were estimated with adding up and homogeneity restrictions imposed.

Consider first the nested tests of the general model against the two nested forms

[8] Results of initial estimation revealed that the computed Box-Pierce χ^2 statistics were high, indicating significant positive serial correlation. See Holt (1998) for alternative autocorrelation parameterizations.
[9] See Kohli (1993, p. 248).

(EGPF and GPF). These tests were conducted using the chi-squared (χ^2) based on Wald test, and the results are illustrated at the end of Table 2. Wald test statistics show that the GPF is dominated by the MGPF and EGPF, demonstrating a rejection of the GPF. Moreover, the freeing up of ϕ is statistically significant, indicating that the MGPF compares favorably with the EGPF. Our preferred model is thus based on the MGPF, and we use its parameter estimates to compute the elasticity estimates.

The detailed parameter estimates for MGPF reported in Table 2 show that, prima facie, each profit-share equation provides a reasonably good fit given the simplicity of the MGPF (noting that estimation is in share form). The R^2 values range from 77.8% for labor input to 99.6% for oil. Autocorrelation diagnostics revealed in the Box-Pierce χ^2 statistics imply that serial correlation in the error terms is no longer severely pathological. This suggests the appropriateness of Moschini and Moro (1994)'s correction for autoregressive errors.

Turning to the regularity properties of the MGPF, we find that most of the parameter estimates satisfy the sufficient conditions in (16). However, the estimated γ_4 is below the limiting value of 0 while that of ρ is above its limiting value of 1; thus the sufficient conditions of monotonicity and curvature properties of the technology are violated. Inspecting the fitted values of the input/output share equations shows that the required monotonicity properties are satisfied over the sample period. More importantly, the estimated own-price elasticities of supply (demand) are consistently positive (negative) in the sample period.[10]

Null Hypotheses Testing on Technical Changes: The estimation results reported in Table 2 provide Wald test results for the null hypotheses concerning the significance of Types I and II technical change. The following comments are in order. First, the existence of Type II technical change $\left(H_0 : \lambda_i = 0 \ \forall \ i\right)$ is supported by the data at the 2.5% level of significance. Second, Type I technical change $\left(H_0 : \tau = 0\right)$ is also supported by the data at the same significant level, implying that the time index should be included in the model. Third, the coefficients of the lagged input price indices λ_1 and λ_2 are positive and statistically significant at the 2.5% level. Recall from (18) that the signs of $\partial \Pi^* / \partial \tilde{w}_{it-1}$ are solely determined by the signs of λ_i. The positive values of λ_1 and λ_2 indicate that increases in the lagged wage rate $\left(\tilde{w}_{1t-1}\right)$ and oil price $\left(\tilde{w}_{2t-1}\right)$ stimulate the Chinese aggregate profit level due to an induced innovation process. This is consistent with Wei et al.'s (2017) conclusion that rising wages is one of the important drivers of China's economic growth. Lastly, the coefficient of time index (τ) is significantly negative, thereby implying that Type I technical change in China has depressed the level of aggregate profit. This finding is fairly striking although it supports the conclusions that China's economic growth has been predominantly driven by input growth and huge investment and that its productivity growth has been seriously slowed down by resource misallocation.[11]

[10] Constrained estimation could be an option to ensure that the global regularity is satisfied. Alternatively, to explore more robust functional forms or incorporate dynamic structures into the model is a fertile area for future research.

[11] See Hsieh and Klenow (2009, p. 1405).

Analysis of the MGPF Elasticity Estimates: Table 3 presents the output/input price and quantity elasticities and time semi-elasticities derived from the parameter estimates of the MGPF for selected years. The first part of Table 3 (Rows 1-6) presents the elasticity estimates measuring the gross effects of output/input prices and capital endowment on domestic production. In general, the estimates of $E_{Y_t^* w_{it}}$ are not very large; the largest (in absolute value) estimate is for output with respect to import prices (Row 5), ranging from -0.988 to -0.698. We note that the elasticities with respect to the capital stock $E_{Y_t^* z_t}$ and output price $E_{Y_t^* p_t}$ (Rows 6 and 1) are highly volatile through time. Interestingly, the elasticity of output supply (Row 1) becomes more elastic after 1995 which coincides with a period when the Chinese government started to implement a series of market-oriented policy reforms.

The estimates of HL own/cross-price and capital input elasticities of input demands are presented in the second (Rows 7-22) and third (Rows 23-26) parts of Table 3 respectively. As expected, all the HL own-price elasticities are negative and most of them are significant at the 1% level, ranging from -2.811 for labor in 1987 (Row 7) to -0.325 for coal in 2005 (Row 17). Considering their absolute values, labor (x_1) and imports (x_4) are clearly own-price elastic while oil (x_2) and coal (x_3) appear to be own-price inelastic. Note that the own-price elasticity of imports $(E_{X_{4t}^* w_{4t}})$ decreases in absolute value varying from -1.458 in 1987 to -1.045 in 2014 (Row 22) whereas the own-price elasticity of other inputs does not monotonically increase or decrease in the same period. Regarding the HL cross-price elasticities, they are generally negative and most of them are highly significant, illustrating gross complementarity between all input pairs. Of particular interest to trade economists is that $E_{X^*_{1t}w_{4t}}$ (Row 10 in Table 3) is negative and large, implying that decreases in import prices due to removal of import controls would stimulate domestic labor demand.

It is worth noting that the input elasticities of capital demand ($E_{X^*_{it}z_t}$ in Rows 23-26) are small and imprecisely estimated. An increase in capital endowment, for example, has negligible effects on all input factor demands judging from the estimated values of $E_{X^*_{it}z_t}$. The signs and magnitude of $E_{X^*_{it}z_t}$ reflect the gross weak complementary relationship between capital & imports and the gross weak substitutability between capital & oil and between capital & coal. On the other hand, the signs of $E_{X^*_{1t}z_t}$ (capital & labor—Row 23) are uncertain, ranging from 0.019 in 1987 to -0.044 in 2014, but all of them are insignificant at 10% level. Therefore, it is difficult to conclude whether capital and labor inputs in China are gross substitutes or complements.

The next set of elasticity estimates (Rows 27-31) show the effects of Type I technical change on output supply $\left(E_{Y^*_t e^t}\right)$ and input demands $\left(E_{X^*_{it} e^t}\right)$. One sees that Type I technical change significantly hurts domestic production and slightly depresses demand for all inputs, although it has a negligible effect on the import demand (Row 31); it also seems to reduce labor much more than oil and coal (Rows 28-30).

As shown in Coelli (1996), the estimates of time semi-elasticities of input demands enable us to calculate the biases $\left(B_{ijt}=E_{X^*_{it}e^t}-E_{X^*_{jt}e^t}\right)$ in technical change; these estimates are reported in Rows (32)-(43) of Table 3. Recall that a positive value of B_{ijt} implies that Type I technical change is Hicks-saving in x_i relative to x_j. Overall, the signs of B_{21t} and B_{4jt} (j = 1, 2, 3) are positive for all observations whilst the estimates of B_{4jt} (Rows 41-43) are significantly different from zero using an asymptotic t-test; these estimates imply that Type I technical change in China has been import saving relative to other inputs. We also read that B_{1jt}, B_{24t} and B_{34t} are negative and B_{1jt} are statistically insignificant for most of the years. Possibly, these results point to the facts that Type I technical change in China is labor using relatively to all other inputs and oil and coal using relatively to imports.

<u>Hicksian Lagged Price Elasticities</u>: Estimates of Hicksian lagged price elasticities $(E_{X_{it}^{H}\tilde{w}_{jt-1}})$ for selected years based on Equation (23) are reported in Table 4. While the lagged own-price elasticities of the demand for labor are negative and small, for most of the years they are statistically significant at the 2.5% level. We may conclude that wage-induced innovation hypothesis receives moderate support in the Chinese data, which is consonant with the nested test results in Table 2. Another way to examine the wage-induced innovation hypothesis is to inspect the signs of $E_{X_{it}^{H}\tilde{w}_{1t-1}} (i = 2, 3, 4)$ in Rows (2)-(4) of Table 4. Not surprisingly, an increase in the lagged long run wage rate stimulates the demand for oil, coal and imports. These findings demonstrate that rising real wage rates in China were the prime cause of labor-saving, oil-using, coal-using and import-using innovations. Nonetheless, own lagged price elasticities of oil $(E_{X_{3t}^{H}\tilde{w}_{3t-1}})$ and imports $(E_{X_{4t}^{H}\tilde{w}_{4t-1}})$ are found to be insignificantly different from zero, indicating that increases in oil or import prices in China do not induce the development and implementation of more efficient technologies in the use of these inputs.

<u>Decomposition of TFP Growth</u>: By using the theoretical framework developed by Karagiannis and Mergos (2000) and Kumbhakar (2002), measures of the output-based total factor productivity growth $\left(\dot{\mathrm{TFP}}_{\mathrm{t}}\right)$ and identifications of its sources can be obtained by using the parameter estimates of a variable profit function. Particularly, totally differentiating the variable profit function $\pi = \Pi^*\left(p_t,\ \mathbf{w}_{\mathrm{t}},\ z_t;\ \tilde{\mathbf{w}}_{\mathrm{t\text{-}1}},\ t\right)$ defined in (8) with respect to t and then dividing both sides by Π^* result in:

$$\frac{d\,log(\pi)}{dt} = \frac{\partial log\left(\Pi^*\right)}{\partial log\left(p_t\right)}\dot{p}_t + \sum_{i=1}\frac{\partial log\left(\Pi^*\right)}{\partial log\left(w_{it}\right)}\dot{w}_{it} + \frac{\partial log\left(\Pi^*\right)}{\partial log\left(z_t\right)}\dot{z}_t$$

$$+\sum_{i=1}\frac{\partial log\left(\Pi^*\right)}{\partial log\left(\tilde{w}_{it}\right)}\dot{\tilde{w}}_{it} + \frac{\partial log\left(\Pi^*\right)}{\partial t}, \qquad (25)$$

where the "·" over a variable indicates its growth rate (log derivative with respect to time).

From the definition of the level of short-run profit, $\pi = p_t y_t - \sum_{i=1}^{N} w_{it}x_{it}$, its total differential with respect to t yields:

$$\frac{d\,log(\pi)}{dt} = \frac{p_t y_t}{\pi}\left(\dot{p}_t + \dot{y}_t\right) - \sum_{i=1}\left(\frac{w_{it}x_{it}}{\pi}\right)\cdot\dot{w}_{it} - \sum_{i=1}\left(\frac{w_{it}x_{it}}{\pi}\right)\cdot\dot{x}_{it}, \qquad (26)$$

where $\dot{y}_t$ and $\dot{x}_{it}$ are the growth rates of output and the ith input respectively. By equating the right hand side of (25) to that of (26), and using Hotelling's lemma, we obtain the following relationship:

$$\frac{\partial log\left(\Pi^*\right)}{\partial log\left(z_t\right)}\dot{z}_t + \sum_{i=1}\frac{\partial log\left(\Pi^*\right)}{\partial log\left(\tilde{w}_{it}\right)}\dot{\tilde{w}}_{it} + \frac{\partial log\left(\Pi^*\right)}{\partial t} = \frac{p_t y_t}{\pi}\left(\dot{y}_t\right) - \sum_{i=1}\left(\frac{w_{it}x_{it}}{\pi}\right)\cdot\dot{x}_{it},$$

which we use to derive the formula of the TFP growth rate $\left(\dot{\mathrm{TFP}}_{\mathrm{t}}\right)$ in the context of the variable profit function; i.e.,

$$\dot{TFP}_t = \dot{y}_t - \sum_{i=1} S'_{it}\dot{x}_{it} - S'_{Z_t}\dot{z}_t$$

$$= \left[\frac{\partial\, log\left(\Pi^*\right)}{\partial t} + \sum_{i=1} E_{\Pi^*\tilde{w}_{it-1}}\dot{\tilde{w}}_{it-1}\right]\frac{\Pi^*}{p_t\left(\frac{\partial\Pi^*}{\partial p_t}\right)} - \frac{\Pi'}{p_t\left(\frac{\partial\Pi^*}{\partial p_t}\right)}\left(\sum_{i=1} S'_{it}\dot{x}_{it} + S'_{Z_t}\dot{z}_t\right), \qquad (27)$$

where $\mathrm{E}_{\Pi^*\tilde{w}_{jt-1}} = \frac{\partial\log(\Pi^*)}{\partial\log(\tilde{w}_{jt-1})}$, $\Pi' = \Pi^* - \frac{\partial\Pi^*}{\partial\log(z_t)}$ is the long run profit function,

$S'_{it} = \frac{-\frac{\partial\Pi^*}{\partial\log\left(w_{it}\right)}}{\mathrm{C}'} = \frac{w_{it}x_{it}}{\mathrm{C}'}$, $S'_{Z_t} = \frac{\frac{\partial\Pi^*}{\partial\log(z_t)}}{\mathrm{C}'} = \frac{P_{z_t}z_t}{\mathrm{C}'}$, $p_{z_t} = \frac{\partial\Pi^*}{\partial z_t}$ is the shadow price of the fixed input, and $\mathrm{C}' = -\sum_{j=1}\left[\partial\Pi^* / \partial\log\left(w_{jt}\right)\right] + \frac{\partial\Pi^*}{\partial\log(z_t)}$ is the long run total cost function.

Recall that the first term in (27) $RTP_t = \left[\frac{\partial\, log\left(\Pi^*\right)}{\partial t}\cdot\frac{\Pi^*}{p_t\left(\frac{\partial\Pi^*}{\partial p_t}\right)}\right]$ refers to the growth rate of Type I technical change whereas the second term $\left(\mathrm{E}_{\Pi^*\tilde{w}_{it-1}}\dot{\tilde{w}}_{it-1}\cdot\frac{\Pi^*}{p_t\mathrm{Y}^*_t}\right)$ describes the input price-induced technical change effect which is positive if an increase in $\tilde{w}_{it-1}$ induces the development of more advanced and efficient technologies.

Estimates of the output-based $\dot{\mathrm{TFP}}_t$, RTP_t, and input price-induced technical change effects in China for the period 1987-2014 are reported in Table 5, with geometric averages for the entire sample period shown in the last row. Focusing on the first column, we find that except for the sub-periods 1993-1997 and 2004-2009, total factor productivity (TFP_t) in China has decreased at an average annual rate of 5.6% which is much lower than the recent estimates in Chen et al. (2018). Clearly, Type I technical change as indicated by the values of RTP_t reported in Column (2) is the root cause of the negative values of conventional $\dot{TFP}_t$ reported in Column (1).

Comparing Columns (3)-(6) of Table 5, it is apparent that wage-induced innovation effect (hereafter $WIIE_t$) (Column 3 of Table 5) is the most important source of input price-induced innovation, and it substantially moderates the gross decline in Type I technical change.[12] Throughout the sample period, the estimates of $WIIE_t$ are positive and large, contributing about 72% of total price-induced innovation, while the estimates of coal and import price-induced innovation effects are negligible.

The computed $\dot{TFP}_t$, RTP_t and $WIIE_t$ from 1987-2014 are plotted in Figure 1. Overall, these series are volatile and do not have a monotonically increasing or decreasing trend. However, there were obvious increases (or declines) of $\dot{TFP}_t$ and $WIIE_t$ over the period 1990-1995 (or 1995-2000). It is important to note that in the sub-period 2010-2014, $WIIE_t$ and $\dot{TFP}_t$ declined from 13.1% to 9.5% and from -7.95% to -9.8%, respectively. These findings can be best explained by noting that after the financial crisis in 2009, despite short-term policy stimulation, the Chinese industrial economy did not successfully transform from the old pattern to the new pattern due to industrial enterprises' lacking the motivation to carry out technological innovation.[13]

6. Concluding Remarks

[12] In notation, $WIIE_t = E_{\Pi^* \tilde{w}_{it-1}} \dot{\tilde{w}}_{it-1} \cdot \frac{\Pi^*}{p_t Y_t^*}$ which measures the rate of technical change induced by an increase in the lagged long run wage rate $\tilde{w}_{1t-1}$.

[13] See Chen et. al. (2018, p.11). Holz (2019) shows that industrial policies in China have little or no effect on investment outcomes in industry.

We present a novel use of a variable profit function to investigate the relationship between total factor productivity (TFP) growth and input price-induced innovation for China. To do so, we implement a new procedure that allows us to capture input price-induced innovation through the explicit incorporation of long-run lagged input prices. Within this framework, we estimate the parameters of a variable profit function to test an induced innovation hypothesis, obtain measures of substitutability among factor inputs, and to derive estimates of TFP growth and its sources.

A quantitative illustration of the results is presented by estimating Cooper et al.'s (2001) MGPF variable profit function for the Chinese economy using published data for the period 1986-2015. The MGPF is appealing for the empirical modeling of input demand and output supply functions, because since it can be easily constrained to be regular over an unbounded region, and because the number of additional parameters to be estimated is small.

There are several interesting results related to alternative nested tests, substitutability measurement, and TFP measurement and decomposition. We first find that the average TFP growth rates (output-based measures) for the entire period are negative (-5.6% per annum) whilst wage and oil price-induced innovations are supported by the data. Moreover, we find that an increase in the lagged wage rate depresses the demand for labor but inflates the demand for oil, coal and imports, demonstrating that sharp increases in real wage rates in China have been the primary cause of labor-saving, oil-using, coal-using and import-using innovations. In addition, results that are of particular interest to trade economists are that labor & imports and capital & imports are found to be gross strong substitutes and gross weak complements respectively. It shows that decreases in import prices may benefit (or hurt) the domestic labor (or capital) sector.

It should be stressed that the wage-induced innovation effect has been the dominant source of productivity growth in China over the period 1987-2014 (10% percent per annum). Without this effect, China's economic growth would have relied almost entirely on massive infusion of physical capital and other factor inputs rather than benefitting from their more efficient utilization. The estimated decline of wage-induced innovation effect after the year 2008 (shown in Column 3 of Table 5) as along with the decline in China's workforce due to population aging raise concerns about prospects for economic growth. This concern accords with recent reports that China's annual GDP growth rate has fallen to about 6–7 percent since 2013. Future sustainable growth in China depends on the acceleration of productivity growth, and domestic innovation would be an essential part of it.[14]

[14] See Wei et. al (2017, p.50).

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Table 1: The Parametric Forms of HL Elasticities and Semi-Elasticities

The HL Output Supply Elasticity: $E_{Y_t^* p_t} = \frac{\partial \log(Y_t^*)}{\partial \log(p_t)} = \eta + \frac{1+\eta}{1+(1+\eta)R_t}$
The HL Input Price Elasticities of Output Supply: $$E_{Y_t^* w_{it}} = \frac{\partial \log(Y_t^*)}{\partial \log(w_{it})} = \frac{-\left\{(1+\eta)\alpha_i + \eta\left[1+(1+\eta)R_t\right]E_{W3w_{it}}\right\}}{\left[(1+\eta)R_t + 1\right]}$$
The HL Fixed Input Elasticity of Output Supply: $E_{Y_t^* z_t} = \frac{\partial \log(Y_t^*)}{\partial \log(z_t)} = \frac{1+\eta}{1+(1+\eta)R_t}$
The HL Lagged Input Price Elasticities of Output Supply: $E_{Y_t^* \tilde{w}_{it-1}} = \frac{\partial \log(Y_t^*)}{\partial \log(\tilde{w}_{it-1})} = \frac{(1+\eta)\lambda_i}{1+(1+\eta)R_t}$
The HL Time Semi-Elasticity of Output Supply: $E_{Y_t^* e^t} = \frac{\partial \log\left(Y_t^*\right)}{\partial t} = \frac{(1+\eta)\cdot\tau}{1+(1+\eta)\cdot R_t}$
The HL Output Price Elasticities of Input Demands: $$E_{X_{it}^{HL} p_t} = \frac{\partial \log(X_{it}^*)}{\partial \log(p_t)} = \frac{p_t^{1+\eta}\left\{(1+\eta)\left[\alpha_i + \eta\cdot R_t\cdot E_{W3w_{it}}\right] + \eta\cdot E_{W3w_{it}}\right\}}{\hat{E}_{it}\cdot W3^\eta}$$
The HL Input Price Elasticities of Input Demands: $$E_{X_{it}^* w_{jt}} = \frac{\partial \log(X_{it}^*)}{\partial \log(w_{jt})} = -\delta_{ij} + \frac{\delta_{ij}\cdot\frac{\gamma_i w_{it}}{z_t^\phi} - \left[\eta\cdot E_{W3w_{it}}\cdot\alpha_j + \eta\left(\alpha_i + \eta\cdot E_{W3w_{it}}\cdot R_t\right)E_{W3w_{jt}} - \eta\cdot R_t\cdot E_{3ijt}\right]\left(p_t^{1+\eta}\big/W3^\eta\right)}{\hat{E}_{it}}$$
The HL Fixed Input Elasticities of Input Demands: $$E_{X_{it}^* z_t} = \frac{\partial \log(X_{it}^*)}{\partial \log(z_t)} = \frac{-\frac{\phi\gamma_i w_{it}}{z_t^\phi} + \frac{\eta p_t^{1+\eta}\cdot E_{W3w_{it}}}{W3^\eta}}{\hat{E}_{it}}$$
The HL Lagged Input Price Elasticities of Input Demands: $$E_{X_{it}^* \tilde{w}_{jt-1}} = \frac{\partial \log(X_{it}^{HL})}{\partial \log(\tilde{w}_{jt-1})} = \frac{\eta\cdot p_t^{1+\eta}E_{W3w_{it}}\lambda_j}{\hat{E}_{it}\cdot W3^\eta}$$
The HL Output Price Elasticities of Input Demands: $$E_{X_{it}^{HL} p_t} = \frac{\partial \log(X_{it}^*)}{\partial \log(p_t)} = \frac{p_t^{1+\eta}\left\{(1+\eta)\left[\alpha_i + \eta\cdot R_t\cdot E_{W3w_{it}}\right] + \eta\cdot E_{W3w_{it}}\right\}}{\hat{E}_{it}\cdot W3^\eta}$$
The HL Time Semi-Elasticity of Input Demands: $E_{X_{it}^* e^t} = \frac{\partial \log\left(X_{it}^*\right)}{\partial t} = \frac{p_t^{1+\eta}\left(\eta\cdot E_{W_3 w_{it}}\cdot\tau\right)}{\hat{E}_{it}\cdot W3^\eta}$

Note: $\hat{E}_{it} = -\partial\Pi\big/\partial\log(w_{it}) = \frac{\gamma_i w_{it}}{z_t^\phi} + p_t^{1+\eta}\left[\alpha_i + \eta E_{W3w_{it}}\cdot R_t\right]\Big/W3^\eta$; δ_{ij} is the kronecker delta; and $E_{3ijt} = \partial E_{W3w_{it}}\big/\partial\log(w_{jt}) = \rho\cdot E_{W3w_{it}}\left(\delta_{ij} - E_{W3w_{jt}}\right)$.

Table 2: Parameter Estimates (asymptotic t ratios in parentheses)

(1)	α_1	0.013 (0.339)	ζ_1	0.892 (38.116)	ρ	1.887 (13.144)
(2)	α_2	0.002 (0.929)	ζ_2	0.071 (4.138)	η	0.386 (4.217)
(3)	α_3	-0.008 (-2.047)	ζ_3	0.037 (4.184)	δ	7.933 (4.883)
(4)	α_4	0.993 (25.167)	ζ_4	0.001 (0.101)	τ	-0.393 (-6.121)
(5)	γ_1	1.476 (1.012)	λ_1	1.210 (2.968)	ϕ	0.403 (2.386)
(6)	γ_2	0.418 (2.668)	λ_2	0.338 (3.569)		
(7)	γ_3	0.929 (3.273)	λ_3	0.158 (1.628)		
(8)	γ_4	-7.562 (-3.032)	λ_4	-0.587 (-1.402)		
	Log likelihood Value					301.523

		R^2	Box-Pierce Statistics ($\chi^2_{6,\ 2.5\%} = 14.449$)
(9)	Output	0.863	4.910
(10	Labor	0.778	4.830
(11)	Oil	0.996	7.310
(12)	Coal	0.962	1.340
(13)	Imports	0.885	4.390

Nested Test Results

	Type of Test	Restriction	Test Statistics	$\chi^2_{2.5\%}$
(14)	Type I Technical Change	$\tau = 0$	37.465	5.024
(15)	Type II Technical Change	$\lambda_i = 0$, i = 1 to 4	30.634	11.143
(16)	EGPF VS GPF	$\eta = 0$	9.112	5.024
(17)	MGPF VS GPF	$\eta = \phi = 0$	20.583	7.378
(18)	MGPF VS EGPF	$\phi = 0$	5.692	5.024

Table 3: Elasticity and Semi-Elasticity Estimates (t ratios in parentheses)

		1987	1995	2005	2014
HL Price and Quantity Elasticities of Output Supply: $E_{Y_t^* ex_{i't}} = \partial \log(Y_t^*) / \partial \log(ex_{i't})$, $\mathbf{ex}_t = (p_t,\ \mathbf{w}_t,\ z_t)$					
(1)	$E_{Y_t^* p_t}$	1.154 (10.427)	1.087 (8.924)	1.381 (8.329)	1.214 (7.165)
(2)	$E_{Y_t^* w_{1t}}$	-0.346 (-3.315)	-0.342 (-3.314)	-0.314 (-2.813)	-0.373 (-3.411)
(3)	$E_{Y_t^* w_{2t}}$	-0.009 (-3.892)	-0.024 (-6.579)	-0.070 (-11.377)	-0.018 (-5.286)
(4)	$E_{Y_t^* w_{3t}}$	-0.022 (-2.747)	-0.023 (-2.977)	-0.008 (-1.234)	0.000 (-0.083)
(5)	$E_{Y_t^* w_{4t}}$	-0.776 (-17.983)	-0.698 (-34.155)	-0.988 (-19.966)	-0.823 (-14.037)
(6)	$E_{Y_t^* z_t}$	0.769 (17.905)	0.702 (34.376)	0.995 (19.981)	0.828 (14.038)
HL Price Elasticities of Input Demands: $E_{X_{it}^* w_{jt}} = \partial \log(X_{it}^*) / \partial \log(w_{jt})$					
(7)	$E_{X_{1t}^* w_{1t}}$	-2.811 (-16.671)	-2.759 (-14.784)	-2.221 (-6.316)	-2.585 (-7.348)
(8)	$E_{X_{1t}^* w_{2t}}$	-0.046 (-4.221)	-0.123 (-4.578)	-0.307 (-4.392)	-0.080 (-5.214)
(9)	$E_{X_{1t}^* w_{3t}}$	-0.141 (-3.881)	-0.144 (-4.201)	-0.051 (-2.774)	-0.019 (-1.881)
(10)	$E_{X_{1t}^* w_{4t}}$	-1.627 (-3.756)	-1.281 (-7.540)	-2.580 (-6.137)	-1.620 (-8.466)
(11)	$E_{X_{2t}^* w_{1t}}$	-1.363 (-5.774)	-1.547 (-10.442)	-1.201 (-7.434)	-1.075 (-9.229)
(12)	$E_{X_{2t}^* w_{2t}}$	-0.896 (-11.059)	-0.950 (-14.642)	-0.973 (-8.796)	-0.627 (-5.114)
(13)	$E_{X_{2t}^* w_{3t}}$	-0.105 (-3.502)	-0.124 (-4.134)	-0.044 (-2.536)	-0.012 (-1.721)
(14)	$E_{X_{2t}^* w_{4t}}$	-1.154 (-4.353)	-1.089 (-12.522)	-2.281 (-15.919)	-0.983 (-7.182)
(15)	$E_{X_{3t}^* w_{1t}}$	-2.045 (-5.142)	-1.568 (-6.176)	-0.617 (-2.897)	-0.463 (-2.270)

Table 3 (Continued)

		1987	1995	2005	2014
(16)	$E_{X^*_{3t}w_{2t}}$	-0.052 (-3.833)	-0.107 (-4.533)	-0.137 (-3.204)	-0.022 (-1.840)
(17)	$E_{X^*_{3t}w_{3t}}$	-0.738 (-2.383)	-0.645 (-2.645)	-0.325 (-0.591)	-0.477 (-0.821)
(18)	$E_{X^*_{3t}w_{4t}}$	-1.977 (-3.260)	-1.199 (-7.250)	-1.661 (-4.473)	-0.723 (-2.832)
(19)	$E_{X^*_{4t}w_{1t}}$	-0.496 (-3.672)	-0.396 (-3.915)	-0.329 (-3.481)	-0.379 (-4.042)
(20)	$E_{X^*_{4t}w_{2t}}$	-0.012 (-3.344)	-0.027 (-6.224)	-0.074 (-11.927)	-0.017 (-6.236)
(21)	$E_{X^*_{4t}w_{3t}}$	-0.042 (-3.696)	-0.034 (-4.599)	-0.017 (-3.928)	-0.007 (-3.381)
(22)	$E_{X^*_{4t}w_{4t}}$	-1.458 (-5.541)	-1.186 (-16.735)	-1.091 (-49.460)	-1.045 (-88.727)
HL Capital Input Elasticities of Input Demands: $E_{X^*_{it}z_t} = \partial\log\left(X^*_{it}\right) / \partial\log(z_t)$					
(23)	$E_{X^*_{1t}z_t}$	0.019 (1.362)	-0.003 (-0.122)	-0.032 (-0.433)	-0.044 (-0.691)
(24)	$E_{X^*_{2t}z_t}$	-0.034 (-0.733)	-0.049 (-1.129)	-0.093 (-1.449)	-0.160 (-2.203)
(25)	$E_{X^*_{3t}z_t}$	-0.130 (-0.849)	-0.178 (-1.265)	-0.522 (-1.573)	-0.589 (-1.500)
(26)	$E_{X^*_{4t}z_t}$	0.170 (1.023)	0.074 (1.352)	0.036 (1.893)	0.018 (2.840)

Table 3 (Continued)

		1987	1995	2005	2014
HL Time Semi-Elasticities of Output Supply and Input Demands: $E_{Y_t^* e^t} = \partial \log(Y_t^*) / \partial t$ **and** $E_{X_{it}^* e^t} = \partial \log(X_{it}^*) / \partial t$					
(27)	$E_{Y_t^* e^t}$	-0.302 (-5.555)	-0.276 (-5.920)	-0.391 (-5.838)	-0.326 (-5.722)
(28)	$E_{X_{1t}^* e^t}$	-0.617 (-3.038)	-0.505 (-4.537	-1.021 -4.164)	-0.641 (-5.149)
(29)	$E_{X_{2t}^* e^t}$	-0.436 (-3.378)	-0.429 (-5.448	-0.902 -6.006)	-0.389 (-4.795)
(30)	$E_{X_{3t}^* e^t}$	-0.752 (-2.762)	-0.472 (-4.673	-0.657 -3.661)	-0.286 (-2.572)
(31)	$E_{X_{4t}^* e^t}$	-0.007 (-3.252)	-0.001 (-3.944	-0.000 -3.064)	-0.000 (-2.384)
Bias in Technological Changes: $B_{ijt} = E_{X_{it}^* e^t} - E_{X_{jt}^* e^t}$					
(32)	B_{12t}	-0.180 (-1.184)	-0.076 (-1.310)	-0.118 (-0.657)	-0.252 (-2.796)
(33)	B_{13t}	0.135 (0.944)	-0.032 (-0.491)	-0.364 (-1.708)	-0.355 (-2.991)
(34)	B_{14t}	-0.609 (-3.012)	-0.504 (-4.534)	-1.021 (-4.164)	-0.641 (-5.149)
(35)	B_{21t}	0.180 (1.184)	0.076 (1.310)	0.118 (0.657)	0.252 (2.796)
(36)	B_{23t}	0.316 (1.451)	0.044 (0.798)	-0.245 (-1.629)	-0.103 (-1.299)
(37)	B_{24t}	-0.429 (-3.327)	-0.428 (-5.445)	-0.902 (-6.006)	-0.389 (-4.795)
(38)	B_{31t}	-0.135 (-0.944)	0.032 (0.491)	0.364 (1.708)	0.355 (2.991)
(39)	B_{32t}	-0.316 (-1.451)	-0.044 (-0.798)	0.245 (1.629)	0.103 (1.299)
(40)	B_{34t}	-0.745 (-2.741)	-0.472 (-4.670)	-0.657 (-3.660)	-0.286 (-2.572)
(41)	B_{41t}	0.609 (3.012)	0.504 (4.534)	1.021 (4.164)	0.641 (5.149)
(42)	B_{42t}	0.429 (3.327)	0.428 (5.445)	0.902 (6.006)	0.389 (4.795)
(43)	B_{43t}	0.745 (2.741)	0.472 (4.670)	0.657 (3.660)	0.286 (2.572)

Table 4: Hicksian Lagged Price Elasticities

		1987	1995	2005	2014
	Hicksian Lagged Price Elasticities of Input Demands: $E_{X_{it}^H \tilde{w}_{jt-1}} = \partial \log\left(X_{it}^H\right) \big/ \partial \log\left(\tilde{w}_{jt-1}\right)$				
(1)	$E_{X_{1t}^H \tilde{w}_{1t-1}}$	-0.447 (-2.535)	-0.479 (-2.757)	-0.145 (-0.611)	-0.345 (-2.366)
(2)	$E_{X_{2t}^H \tilde{w}_{1t-1}}$	14.989 (2.148)	4.906 (2.511)	2.518 (2.125)	6.773 (2.564)
(3)	$E_{X_{3t}^H \tilde{w}_{1t-1}}$	3.281 (1.323)	1.935 (1.442)	4.570 (1.442)	5.830 (1.577)
(4)	$E_{X_{4t}^H \tilde{w}_{1t-1}}$	0.857 (1.312)	0.753 (1.383)	1.400 (1.387)	0.901 (1.376)
(5)	$E_{X_{1t}^H \tilde{w}_{2t-1}}$	-1.810 (-2.804)	-1.660 (-2.935)	-2.142 (-2.898)	-1.388 (-2.754)
(6)	$E_{X_{2t}^H \tilde{w}_{2t-1}}$	-0.143 (-2.782)	-0.125 (-2.996)	-0.021 (-0.462)	-0.078 (-1.897)
(7)	$E_{X_{3t}^H \tilde{w}_{2t-1}}$	-0.156 (-1.478)	-0.082 (-1.431)	0.758 (1.450)	0.084 (0.967)
(8)	$E_{X_{4t}^H \tilde{w}_{2t-1}}$	0.893 (1.396)	0.841 (1.390)	1.340 (1.383)	0.706 (1.379)
(9)	$E_{X_{1t}^H \tilde{w}_{3t-1}}$	-2.031 (-2.539)	-1.367 (-2.759)	-0.877 (-1.319)	-0.015 (-0.025)
(10)	$E_{X_{2t}^H \tilde{w}_{3t-1}}$	0.702 (1.521)	0.052 (0.694)	-0.110 (-0.774)	0.124 (0.811)
(11)	$E_{X_{3t}^H \tilde{w}_{3t-1}}$	0.016 (0.308)	-0.006 (-0.232)	0.128 (1.176)	0.108 (1.069)
(12)	$E_{X_{4t}^H \tilde{w}_{3t-1}}$	1.040 (1.304)	0.708 (1.277)	0.496 (0.938)	0.021 (0.070)
(13)	$E_{X_{1t}^H \tilde{w}_{4t-1}}$	-1.529 (-2.458)	-1.276 (-2.847)	-1.316 (-2.922)	-1.195 (-2.950)
(14)	$E_{X_{2t}^H \tilde{w}_{4t-1}}$	0.149 (0.471)	-0.339 (-3.245)	-0.367 -3.509	-0.334 (-3.567)
(15)	$E_{X_{3t}^H \tilde{w}_{4t-1}}$	-0.072 (-0.715)	-0.159 (-1.608)	-0.169 -1.610	-0.155 (-1.613)
(16)	$E_{X_{4t}^H \tilde{w}_{4t-1}}$	0.766 (1.444)	0.621 (1.428)	0.639 1.408	0.580 (1.402)

Table 5: Decomposition of TFP Growth, China 1987-2014

Year	(1) $\dot{TFP}_t$	(2) Type I (RTP_t)	(3) Type II - Labor	(4) Type II - Oil	(5) Type II - Coal	(6) Type II - Imports
1987	-11.51%	-21.80%	10.16%	0.00%	0.86%	-1.47%
1988	-12.24%	-25.85%	10.87%	0.00%	0.96%	-0.51%
1989	-12.56%	-25.88%	11.76%	0.74%	0.80%	-2.40%
1990	-7.26%	-24.32%	10.69%	2.50%	0.51%	-0.58%
1991	-6.46%	-25.57%	6.62%	4.25%	2.80%	0.60%
1992	-6.57%	-28.02%	5.74%	5.30%	2.66%	2.50%
1993	-5.04%	-28.21%	8.13%	3.08%	2.66%	0.91%
1994	3.52%	-26.15%	16.26%	1.34%	2.13%	-0.57%
1995	14.41%	-19.90%	17.81%	15.11%	1.52%	-0.73%
1996	4.47%	-15.76%	14.99%	5.58%	1.11%	-0.69%
1997	0.75%	-14.55%	11.05%	4.16%	0.79%	-0.04%
1998	-6.61%	-14.68%	7.29%	0.61%	0.68%	0.07%
1999	-9.51%	-16.10%	4.68%	0.97%	0.45%	0.97%
2000	-12.60%	-18.78%	3.36%	2.26%	-0.28%	-0.16%
2001	-10.70%	-19.28%	3.08%	5.63%	-0.59%	-0.67%
2002	-11.43%	-21.48%	4.17%	3.65%	-0.13%	-0.08%
2003	-9.50%	-25.27%	6.05%	2.06%	0.81%	0.25%
2004	-10.01%	-29.61%	7.54%	0.13%	0.97%	0.11%
2005	-6.75%	-28.32%	9.77%	3.48%	0.84%	-1.77%
2006	-0.81%	-27.34%	11.49%	7.18%	1.70%	-0.18%
2007	0.31%	-26.42%	12.71%	6.36%	2.02%	0.74%
2008	-2.64%	-26.06%	14.00%	4.15%	1.66%	0.82%
2009	-4.11%	-19.82%	11.59%	2.63%	0.76%	-1.07%
2010	-7.95%	-25.43%	13.06%	-1.69%	0.47%	1.94%
2011	-4.81%	-25.36%	11.39%	-0.31%	4.35%	-0.89%
2012	-5.57%	-22.27%	9.89%	0.49%	2.77%	0.09%
2013	-6.29%	-22.49%	9.88%	3.60%	1.64%	-1.37%
2014	-9.77%	-23.49%	9.47%	1.43%	-0.76%	1.67%
1987-2014	-5.62%	-23.15%	9.77%	3.03%	1.22%	-0.09%

Notes: (1) Column 1 is computed from equation (27); (2) Columns 2-6 are the components of equation (27); (3) Column 2: $\frac{\partial \, log\left(\Pi^*\right)}{\partial t} \frac{\Pi^*}{p_t\left(\frac{\partial \Pi^*}{\partial p_t}\right)}$; (4) Columns 3-6: $\mathrm{E}_{\Pi^* \tilde{w}_{it-1}} \dot{\tilde{w}}_{it-1} \frac{\Pi^*}{p_t \mathrm{Y}_t^*}$ (i = 1···4, respectively)

Figure 1: Price-Induced Technical Change