Productivity in China's High Technology Industry: Regional Heterogeneity and R&D

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Abstract

This paper analyzes the impact of Research and Development (R&D) on the productivity of China's high technology industry. In order to capture important differences in the effect of R&D on output that arise from geographic and socioeconomic differences across three major regions in China, we use a novel semiparametric approach that allows us to model heterogeneities across provinces and time. Using a unique provincial level panel dataset spanning the period 2000-2007, we find that the impact of R&D on output varies substantially in terms of magnitude and significance across different regions. Results show that the eastern region benefits the most from R&D investments, however it benefits the least from technical progress, while the western region benefits the least from R&D investments, but enjoys the highest benefits from technical progress. The central region benefits from R&D investments more than the western region and benefits from technical progress more than the eastern region. Our results suggest that R&D investments would significantly increase output in both the eastern and central regions, however technical progress in the central region may further compound the effects of R&D on output within the region.

Keywords: China, Research and Development (R&D), Productivity, Semiparametric smooth coefficient model (SPSCM)

1. Introduction

In 2007, China's high technology industry (consisting of, for example, the pharmaceutical sector, aviation, electronics and communication, computer and office supplies, and medical equipment and instruments) accounted for approximately 20% of manufacturing within China, but about 45% of total Chinese exports (China Statistical Yearbook on High Technology Industry [1] and China Statistical Yearbook [2]). The prominence of the high technology industry in Chinese exports is primarily because of rising labor costs in other sectors of the Chinese economy, making other industries less competitive in international markets. Hence, this industry will continue to be an important component of Chinese exports in future years.

Despite the broad success of the high technology industry, there are substantial regional differences in the productivity of the high technology industry across China. In total, China has 31 provinces, autonomous regions, and municipalities, leading to substantial geographical differences and differences in natural resource endowments that ultimately effect the investment in and pro-

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ductivity of firms.[1] Typically, China is divided into three broad regions - the eastern, central, and western regions. The eastern region includes 11 provinces along the east coast of China, with an area of 1,294,000 square kilometers, accounting for 13.5% of the total area of China. The eastern region is rich in resources, such as seafood, fossil fuels, iron ore and minerals. The abundance of resources and access to the coast has made the eastern region the primary region for economic development in China. The central region includes 8 provinces, with an area of 2,818,000 square kilometers, accounting for 29.3% of the total area of China. This region is rich in various metal and non-metal resources, leading primarily to the development of heavy industry. The western region includes 12 provinces, with an area of 5,414,000 square kilometers, accounting for 56.4% of the total area of China. This region has a complex terrain with limited transportation and investment to the extent that, only until recently, there has not been much development and investment in these provinces. Figure 1 shows a map of China that clearly labels each of the three regions.[2]

The wide disparity in investment across each of the regions has led to a substantial disparity in GDP per capita. In the western region (specifically Guizhou), GDP per capita in 2007 was estimated to be about 6915 *renminbi* (RMB; Chinese currency). In Beijing (located in the eastern region), GDP per capita in the same year was about 58204 RMB (China Statistical Yearbook [2]). Hence, the differences in economic development across regions has led to considerable differences in population well-being.

In addition to the vast divergence in overall economic development across the three regions, the past several decades have witnessed a substantial divergence in terms of the development of the high technology industry across the eastern, central, and western regions in China. In 2007, the value-added of the high technology industry in the eastern region accounted for 88.9% of the total value-added in China, while the central and western regions only accounted for 6.5% and 5.6%, respectively (China Statistical Yearbook on High Technology Industry [1]). Moreover, exports from the high technology industry in the eastern region accounted for 97.9% of the total high technology exports from China, while the central and western regions only accounted for 1.34% and 0.77%, respectively. That is, following other trends in Chinese investment and development, the high technology industry is almost entirely located in the eastern region of the country.

In particular, research and development (R&D) is vitally important to the high technology industry. According to the Organization for Economic Co-operation and Development (OECD [3]), R&D refers to "creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications." In 2007, the R&D inventory in the high technology industry in the eastern, central, and western regions accounted for 83.7%, 6.7%, and 9.6%, respectively, of the total R&D inventory in the high technology industry in China (China Statistical Yearbook on High Technology Industry [1]). Furthermore, the percentages of patents in the high technology industry held in the three regions are 86.6, 6.6, and 6.8, respectively, for the eastern, central, and western regions. The broad discrepancies in R&D investments in China have considerable policy

[1] Chinese regional and provincial level statistics, including the ones summarized below, are available online from the National Bureau of Statistics of China. See http://www.stats.gov.cn/english/ for further details and statistics.

[2] Map source: $http://www.chinamapxl.com/regional-map.html$.

implications for Chinese development and growth. For example, because the eastern region is already highly developed, further investments in the high technology industry and R&D are likely to be more and more costly over time, as the prices of productive inputs rise. This suggests that the return on investments in the central and western regions may potentially be higher than in the eastern region. Conversely, the lack of established infrastructure in the central and western regions suggests that factors of production are likely to be cheaper, and potentially more productive than their counterparts in the eastern region. Therefore, it is not necessarily clear as to where investments in R&D will have the highest return.

The goal of this paper is to estimate the relationship between R&D and the productivity of the high technology industry in China through a production function framework, and through this lens ascertain in which provinces or regions R&D investments may draw the highest returns in terms of firm productivity. Based on the fact that the regions in China are heterogeneous in terms of their economic development, social characteristics, geographical locations, and resource endowments, a standard production function framework that assumes all regions are identical cannot accurately model the relationship between R&D and the productivity of the high technology industry. Therefore, our primary approach generalizes the standard framework in order to accommodate heterogeneity in the effect of R&D on output across regions. This approach allows for more accurate estimation of the effect of R&D on firm productivity, and thus provides direction for future investments in R&D in China.

2. Theoretical Framework

2.1. Production Functions

Since we use a production function as a tool to examine the nexus between R&D and productivity, we provide a brief discussion on production functions in this subsection. A production function in economics describes the technology (in mathematical form) that transforms various inputs into output or outputs. In a single output case the production technology can be expressed as:

$$Y = A(t)f(X_1, X_2, \ldots, X_K) \tag{1}$$

in which Y is the firm's output, X_k ($k = 1, \ldots, K$) are inputs used, $f(\cdot)$ is the production technology (black box) that defines the process by which inputs are transformed into output, A is the technological (shift) parameter, and t denotes time. Often, the technological parameter of the firm is assumed to be time dependent in order to capture the notion that firms can increase their output over time through experience (learning by doing).

In applied production analysis, it is often helpful to specify the functional form of $f(\cdot)$, in order to obtain parameters of the underlying production process using observable data. A popular choice of production function is the Cobb-Douglas (Cobb and Douglas [4]). The Cobb-Douglas production function is written as:

$$f(\cdot) = X_1^{\beta_1} \times X_2^{\beta_2} \times \cdots \times X_K^{\beta_K} = \prod_{k=1}^{K} X_k^{\beta_k} \tag{2}$$

in which β_k are unknown parameters that determine the impact of input X_k on output. Many other functional forms can be used to represent the production technology. Substituting the Cobb-Douglas form (2) in (1) gives the following form of the production technology:

$$Y = A(t) \prod_{k=1}^{K} X_k^{\beta_k}. \tag{3}$$

To simplify econometric estimation of (3) it is often expressed in natural logarithm form with the addition of a stochastic noise term u, viz.,

$$\ln Y = \beta_0(t) + \sum_{k=1}^{K} \beta_k \ln X_k + u, \tag{4}$$

in which $\beta_0(t) = \ln A(t)$. The advantage of using the log transformation is that the production function is now linear with respect to the unknown parameters, and is simple to estimate using ordinary least squares (OLS). The parameters, β_k, can now be interpreted as an input elasticity: a 1% increase in the level of X_k used by the firm leads to a β_k% change in output. In addition, the sum of the coefficients also has a meaningful interpretation. If, for example, $\sum_k \beta_k = 1$, then the production function has constant returns to scale, meaning that if all inputs are simultaneously doubled, output will also be doubled. If $\sum_k \beta_k > 1$ (or < 1), then doubling all inputs will more than (or less than) double output, thereby meaning that the returns to scale is greater (less) than unity, i.e., increasing (decreasing) returns to scale.

Figure 2 provides a simple graphical illustration of a production function, assuming that the firm is producing output using only one input. For any given time period, e.g., $t = t_0$, we can see that increasing inputs increases output by traveling northeast along the curve. However, over time the technology can change and this can be illustrated by shifting (usually upward) the technological parameter in the production function. The figure shows that the firm is able to produce a greater amount of output over time using the same amount of the input. Thus, time can be viewed as an environmental factor which is different from the standard (conventional) inputs. Traditional inputs are capital (e.g., machines), labor (e.g., manpower), energy, and raw materials. Environmental factors change output by changing the environment, thereby affecting productivity of the traditional inputs. Hence, it is important to differentiate the environmental factors from the traditional inputs.

In addition to time, other factors may influence the production process (i.e., shift the production function). In this paper, we follow Li et al. [5] and model R&D as an another important environmental factor. By itself, R&D may not be capable of producing output (i.e., R&D is not a traditional input), but further investment in R&D is likely to affect the ability of the firm to transform inputs into outputs more effectively. We point out that producer theory is typically silent when it comes to incorporating environmental variables in a production function. Although these are recognized as shift variables, it is not clear whether these shifts are neutral or not. If the shift is neutral, these environmental variables can be introduced in the technology parameter, i.e., $\beta_0(t, R\&D)$. There is, however, no reason to believe that the shift in the production function is neutral. That is, the environmental variables are likely to influence the productivity of traditional inputs (e.g., capital and labor). Because of this we prefer to include the environmental variables into the model by allowing the elasticities of capital and labor to vary with respect to these variables.

2.2. Contribution to the Literature

Following the seminal article by Griliches [6], there has been an extensive literature analyzing the impact of R&D activities on firm productivity. Some recent contributions include Griliches [7], Griliches [8], Hall and Mairesse [9], Griliches [10], Griffith et al. [11], Hu and Jefferson [12], Klette and Kortum [13], Hu et al. [14], Jefferson et al. [15], Lööf and Heshmati [16] and Wu [17]. In general, empirical research shows that R&D positively and significantly impacts productivity (e.g., Hall and Mairesse [9], Griffith et al. [11], Hu and Jefferson [12]). However, results from studies that use Chinese data have been mixed; some studies find a positive effect of R&D (e.g., Hu et al. [14], Jefferson et al. [15] and Wu [17]) and others fail to find a positive effect (e.g., Zhang [18] and Li [19]). We surmise that the lack of empirical consensus regarding the impact of R&D on productivity in China is possibly because of large regional disparities in economic development, technology, and human resources across different Chinese provinces. We therefore use Chinese provincial level data to focus on China's high technology industry, and measure the impact of R&D on industry productivity across different Chinese provinces.

Previous studies have found that R&D significantly impacts productivity in various Chinese manufacturing sectors; Wu [17], Jefferson et al. [15] and Hu et al. [14] find evidence that R&D significantly affects productivity. Wu [17] estimates the elasticity of output with respect to R&D using an industry level panel dataset spanning the period 1993-2002. He finds that the elasticity of output with respect to R&D is approximately 0.4-0.67 for China's high technology industry, while it is higher in industries with larger average firm size and a smaller fraction of state-owned enterprises. Jefferson et al. [15] use a recursive three-equation model to analyze a panel dataset on large and medium sized manufacturing enterprises in China over the period 1997-1999. He finds strong evidence of positive contributions of R&D expenditure on productivity, with an output elasticity with respect to R&D of approximately 0.24. He also finds that there are substantial differences in the return to R&D across firms with different types of ownership. Using a Cobb-Douglas production function framework and an unbalanced sample of approximately 10,000 large and medium sized manufacturing firms in China over the period 1995-1999, Hu et al. [14] find evidence in favor of productivity of R&D in the high technology sector (the estimated elasticity is approximately 0.064), but no significance of R&D on productivity in other sectors.

Other studies find opposite results. Using data envelopment analysis (DEA), Li [19] shows that the effect of R&D on output is negative. Zhang [18], using the same method as Li [19], finds that R&D has no significant effect on the total factor productivity of Chinese manufacturing industries. By splitting the industries or firms into different categories (e.g., high technology versus low technology sectors, firm size, or foreign versus state-owned firms) Wakelin [20] and Tsai and Wang [21] find that there are substantial differences in the impact of R&D on productivity growth and the elasticities of labor and capital across different categories.

We focus on measuring the impact of R&D, capital, labor, and time on the productivity of China's high technology industry to assess whether the impact of these factors on output varies substantially across different provinces and regions. While R&D and time are generally considered to be important factors to account for when estimating industry productivity, it is difficult to justify their inclusion as inputs into the production function. Typically, economists think of R&D and time as being important environmental variables that influence the productivity of traditional inputs, such as capital and labor. Using a simple Cobb-Douglas production function with capital and labor as traditional inputs, we generalize the model to allow the parameters associated with inputs to vary with R&D and time. In the standard Cobb-Douglas production model no distinction is made between traditional and environmental variables and the output elasticity of each input is constant for all provinces and for every year. A generalization of the Cobb-Douglas function to the translog allows the output elasticities of the inputs to vary linearly with respect to all inputs. Here we use the Cobb-Douglas model for simplicity but generalize it so that the coefficients (i.e., elasticities) on the traditional inputs (i.e., capital and labor) vary with respect to certain environmental factors, namely R&D and time, while controlling for fixed province effects. The advantage of our approach is that it incorporates R&D and time into the production process, without resorting to a specification that treats these environmental factors as traditional inputs into the production process. We used a semiparametric smooth coefficient model (Cai et al. [22]) to estimate our generalized Cobb-Douglas production specification,[3] and compare the results against a fully parametric model.

In addition to incorporating R&D and time into the regression model in an arguably more appropriate fashion (i.e., not as traditional inputs into the production function), the generalized production function framework allows for heterogeneity in the coefficients on capital and labor (i.e., the elasticities of capital and labor) since these coefficients are functions of environmental factors which affect the production function non-neutrally. An additional insight that comes from the semiparametric model is that for a given level of the environmental variables (e.g., a given level of R&D), the model is reduced to the standard constant coefficient Cobb-Douglas model (Hartarska et al. [25]). Moreover, the semiparametric model provides further flexibility in the estimated coefficients because it does not require specification of any parametric functional form for the coefficients. Such parameter heterogeneity is crucial when analyzing productivity in China, since rapid growth and recent structural transitions in China have left a substantial gap in the level of economic development across provinces.

3. Methodology and Data

3.1. Econometric Methodology

Models of industry productivity typically require the specification of the industry production function. As mentioned previously, the Cobb-Douglas production function in logarithmic form is commonly used in practice. That is, the function being estimated is:

$$\ln Y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln X_{kit} + u_{it}, \tag{5}$$

where Y_{it} is the output of industry i at time t, X_{kit} is the level of input k for industry i at time t, and u_{it} is a random error. While the Cobb-Douglas framework provides a reasonable benchmark

[3] We note that the semiparametric smooth coefficient model has been used previously, for example, Mamuneas et al. [23] and Asaftei and Parmeter [24].

production function in applied research, it is often restrictive in its assumptions of strict parameter homogeneity. Hence, instead of estimating the traditional Cobb-Douglas production function, we make three generalizations to the model in (5) that incorporate heterogeneity in the intercept and elasticities of capital and labor, while maintaining the basic Cobb-Douglas structure.

Our first generalization, which we refer to as Model 1, is to make the intercept, β_0, a parametric function of various environmental factors. The advantage of Model 1 over the traditional model is to allow for industry heterogeneity via the intercept term, and is written as:

$$\ln Y_{it} = \beta_0(Z_{it}; \theta_0) + \sum_{k=1}^{K} \beta_k \ln X_{kit} + u_{it}, \tag{6}$$

in which θ_0 denotes a vector of parameters to be estimated, and Z_{it} includes both continuous and discrete exogenous environmental variables. If $\beta_0(Z_{it}; \theta_0) = \alpha_0^0 + \sum_{l=1}^{L} \alpha_l^0 Z_{lit} + \mu_i$, in which Z_{lit} denotes the l-th continuous environmental factor of industry i at time t, and μ_i is the industry-specific fixed effect (which can be treated as a dummy variable) the model can be estimated via a least-squares dummy variable (LSDV) approach (Baltagi [26]). The marginal effect of Z_{lit} on the intercept is captured by α_l^0. However, we can generalize the traditional model a bit further by allowing the elasticities to be parametric functions of the same environmental factors, in addition to the intercept. This gives rise to Model 2:

$$\ln Y_{it} = \beta_0(Z_{it}; \theta_0) + \sum_{k=1}^{K} \beta_k(Z_{it}; \theta_k) \ln X_{kit} + u_{it}, \tag{7}$$

in which $\beta_k(Z_{it}; \theta_k) = \alpha_0^k + \sum_{l=1}^{L} \alpha_l^k Z_{lit} + \mu_i$, $\forall k = 1, 2, \ldots, K$. Thus α_l^k captures the marginal effect of Z_{lit} on the elasticities. Model 2 allows both the intercept and elasticities of capital and labor to vary with respect to environmental factors, and thus constitutes a substantial generalization of the traditional model. Although the dummy variables interact with $\ln X_{kit}$ in this model, the LSDV approach still applies here. However, Model 2 imposes potentially restrictive parametric assumptions regarding the way in which heterogeneity is introduced into the model; in general, specific functional forms for the coefficients are unknown to the econometrician. Thus, our third model incorporates heterogeneity in the intercept as well as capital and labor elasticities without requiring the practitioner to specify the functional form of the coefficient functions. That is, we assume the intercept and capital and labor elasticities are unknown smooth functions of the environmental factors, Z_l, and fixed effects, to be estimated nonparametrically. Known as the semiparametric smooth coefficient model (see Cai et al. [22] and Li et al. [5]), we write our Model 3 as:

$$\ln Y_{it} = \beta_0(Z_{it}) + \sum_{k=1}^{K} \beta_k(Z_{it}) \ln X_{kit} + u_{it}, \tag{8}$$

in which $Z_{it} = (Z_{1it}, \ldots, Z_{Lit}, \mu_i)$ is an $(L+1) \times 1$ vector, μ_i are the fixed effects, $\beta_j(Z_{it})$ $\forall j = 0, \ldots, K$ are the unknown smooth coefficient functions to be estimated.

While Models 1 and 2 can be estimated using OLS, Model 3 must be estimated using nonparametric methods. Following Li and Racine [27], we use the local-linear least-squares procedure to estimate the unknown coefficient functions. Specific details regarding the local-linear least-squares estimator can be found in the technical appendix to this paper or in Li and Racine [27].

Two aspects of our econometric approach are worth emphasizing. First, the local-linear procedure used to estimate the unknown coefficient functions also (simultaneously) provides estimates of the first order derivatives of the coefficient functions with respect to the continuous environmental factors (i.e., z^c). Second, an interesting feature of the smooth coefficient model is that the estimated parameters (functions) differs from the OLS estimates only through the inclusion of the kernel function. Elimination of the kernel function in (14) reduces the estimator to simple OLS, and subsequently reduces Model 3 to the traditional Cobb-Douglas model given in (5).

3.2. Data Construction

The dataset is constructed from the China Statistical Yearbook [2] and the China Statistical Yearbook on High Technology Industry [1], and is a unique panel of 25 provinces and four municipalities (Beijing, Tianjin, Shanghai, and Chongqing) spanning the period 2000-2007.[4] Our dataset differs from the datasets used by Wu [17] and Hu et al. [14], who used industry-level and firm-level panels to study Chinese manufacturing. We do not use firm level data because they are not available for many small-sized firms and for every province in China. In order to better understand regional heterogeneity in the impact of R&D on productivity across regions in China, we use provincial level data because it provides more comprehensive coverage of output across Chinese provinces.

Output is measured as real value-added goods and services in thousands of RMB in China's high technology industry, deflated by the Producer Price Index (PPI). Production involves two inputs: the number of employees and the inventory of real physical capital in thousands of RMB, deflated by the Price Index for Investment in Fixed Assets. We include real R&D inventory in thousands of RMB, a time trend, and an indicator for region as one of the environmental factors.

As productivity appears to be affected by the accumulated stocks of capital and R&D expenditure, stock indicators (rather than current or lagged flows) were used as impact variables; see for example, Hulten [28], Jorgenson [29], Hall and Mairesse [9], Bönte [30]. Accordingly, R&D and the stock of physical capital are computed using the perpetual inventory method based on the following equations:

$$R_{t_0} = \frac{E_{t_0}}{g_R + \delta_R}, \quad t_0 = 1999 \tag{9}$$

$$R_t = R_{t-1}(1 - \delta_R) + E_t, \quad t = 2000, \ldots, 2007 \tag{10}$$

in which R is R&D inventory, E is R&D expenditure, g_R denotes the compound average rate of change in real R&D expenditure, and δ_R denotes the depreciation rate for R&D inventory.

Similarly,

$$K_{t_0} = \frac{I_{t_0}}{g_K + \delta_K}, \quad t_0 = 1999 \tag{11}$$

$$K_t = K_{t-1}(1 - \delta_K) + I_t, \quad t = 2000, \ldots, 2007 \tag{12}$$

in which K is the inventory of physical capital, I is physical capital expenditure, g_K denotes the

[4] Xinjiang and Tibet are excluded from the sample because of a lack of data availability.

compound average rates of change in fixed capital expenditure, and δ_K denotes the depreciation rate for the stock of physical capital.

To obtain g_R and g_K, we calculate the compound average rates of change in real R&D expenditure and fixed capital expenditure for every province over the period 2000-2007. We set the depreciation rate for R&D (δ_R) equal to 15% following previous studies (for example, Schankerman and Pakes [31], Hall and Mairesse [9], and Hall [32]). Other studies (for example, Musgrave [33], Bischoff and Kokkelenberg [34], and Nadiri and Prucha [35]) assume the depreciation rate for physical capital (δ_K) is approximately 6%, however we use 10% as the depreciation rate for physical capital because technologically advanced sectors are known to have shorter product life-cycles and higher scrapping rates. With the exception of the time trend and regional indicator, all variables are measured in logs.

Table 1 provides a brief summary of the variables used in our analysis. As can be seen from Table 1, there are large discrepancies in terms of economic development across different regions. Hence a regional analysis is appropriate when analyzing Chinese data. We classify the data into three different regions (i.e., the eastern, central, and western regions) based on geographical location, natural resources, economic development, and social characteristics.[5]

4. Results and Policy Implications

4.1. Parametric Results and Model Selection

We now present our results from each of our production function specifications. Table 2 summarizes the results from each of the three models: the elasticity of output with respect to capital ($\hat{\beta}_1$) and labor ($\hat{\beta}_2$), returns to scale, the elasticity of output with respect to R&D ($\partial \ln Y/\partial \ln Z_1$) and technical change ($\partial \ln Y/\partial t$). Since Models 2 and 3 give rise to observation specific estimates, we summarize the results from these models by reporting the estimates at the mean, 25th (Q1), 50th (Q2), and 75th (Q3) percentiles.

In Model 1, R&D and time only neutrally shift the production function, while R&D and time are allowed to non-neutrally affect the production function in Models 2 and 3. Hence, the elasticity of output with respect to capital and labor are invariant with respect to R&D and time in Model 1, but are allowed to vary with respect to R&D and time in Models 2 and 3.

Results across each of the three models are generally consistent. We find the elasticity of output with respect to capital ($\hat{\beta}_1$) and labor ($\hat{\beta}_2$) to be generally positive and significant across each of the three models. We note that both elasticities are negative and significant at the 25th percentile for Model 2, the fully parametric model. In the semiparametric model, all the quartile values of capital and labor elasticities are positive, and the magnitudes of the elasticities are in line with macroeconomic theory: the share of income going to physical capital is about 1/3 and the share of income going to labor is about 2/3. Technical progress is positive and significant across each of the models, and returns to scale, the sum of $\hat{\beta}_1$ and $\hat{\beta}_2$, is closest to unity in the semiparametric

[5] The eastern region includes Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Hebei, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western region includes Neimenggu, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, and Ningxia.

model. We find evidence of decreasing returns to scale across each of the three models, except at the 75th percentile for Model 2. In addition, we find much greater variability in the returns to scale estimates in Model 2 than in Model 3. Nevertheless, both Models 2 and 3 suggest substantial heterogeneity in the coefficients and returns to scale across the observations in this sample.

We find the effect of R&D on output to be insignificant in Model 1, mostly insignificant (sometimes even negative) in Model 2, but always positive and significant in Model 3. Note that the magnitudes of the R&D elasticity is substantially larger in Model 3 compared to Models 1 and 2. A glance at the technical change measure suggests that the effects of R&D are mostly absorbed by the time effect in the two parametric models.

In light of the fact that both Models 2 and 3 suggest substantial heterogeneities across the observations in our sample, yet different models yield substantial variation in terms of the estimates (i.e., magnitude, sign, and significance), we may rely on economic and statistical criteria to select the preferred model. Table 3 reports the cross-validated optimal bandwidths for the Z variables in the semiparametric model, along with percentage of violations in both parametric and semiparametric models for comparison. We expect both $\hat{\beta}_1$ and $\hat{\beta}_2$ to be positive (as input elasticities); violations occur when the estimates are negative. We can see that in the parametric model nearly 30% of the elasticities are negative for both capital and labor, while the semiparametric model yields far fewer violations (no violations for $\hat{\beta}_2$). This motivates the semiparametric model as more appropriate than its parametric counterpart from an economic point of view. The third row of the table reports twice the standard deviation (σ_z) of the continuous Z variables. We compare twice the standard deviation with the optimal bandwidth: for local-linear regression, the rule-of-thumb for each continuous Z variable to enter the model non-linearly is that the bandwidth is less than $2 \times \sigma_z$, which is shown in the table. For discrete regressors (i.e., the regional indicator), if the bandwidth is less than $c/(c-1)$, where c is the number of categories the variable can take, then the regressor is a relevant predictor of the unknown function. We find that the optimal bandwidth on the regional indicator is less than the upper bound. This implies that a regional fixed effect is not entering into the coefficient function in a linearly and additively separable fashion, as is typically assumed in parametric models of panel data. Hence, examination of the bandwidths suggests that a linear parametric function would not accurately capture the data generating process. To formally test for correct specification to choose our preferred model, we use the model specification test proposed by Cai et al. [22] to determine which model best fits the data. Results from the model specification tests reject the hypothesis that the coefficients are linear parametric functions of the environmental variables with a p-value equal to 0.0000. Hence our preferred specification, and the focus of the rest of this paper, is the semiparametric generalization, Model 3.

4.2. Semiparametric Results

4.2.1. The Elasticities of Capital and Labor

Figure 3 displays each of the partial effects from the semiparametric model, along with bootstrapped confidence bounds for each partial effect. The advantage of reporting partial effects at the mean (or quartile) values is limited because we are unable to see statistical significance for the partial effect of each observation. Hence the objective of the plots is to report statistical significance for each observation of the partial effects obtained from the semiparametric model.

To understand these plots consider the following procedure for constructing these plots for any given estimate, say for example $\hat{\beta}_1$. First, plot $\hat{\beta}_1$ against $\hat{\beta}_1$; this plots $\hat{\beta}_1$ along the 45 degree line. Then, adding (or subtracting) twice the standard error from $\hat{\beta}_1$ gives the upper (or lower) confidence bounds. Plot both the upper and lower confidence bounds against $\hat{\beta}_1$. Thus, for every partial effect placed on the 45 degree line, we also can see an observation-specific confidence interval. If the horizontal line at zero passes inside of the confidence bounds for any given observation, then the partial effect for this observation is statistically insignificant. Conversely, if the horizontal line at zero passes outside of the confidence bounds, then the partial effect for this observation is statistically significant. In addition to showing statistical significance for each partial effect, the plots show the sign of the partial effects as well as their density. If any given partial effect is to the right of the vertical line at zero, it is positive; otherwise it is negative. Observations that lie in close proximity to each other are located in areas of higher density, whereas observations that do not lie in close proximity to others are located in areas of lower density.

From Figure 3, we can see that for $\hat{\beta}_1$ and $\hat{\beta}_2$, most of the lower bounds are greater than zero, indicating that for most of the observations the elasticities of capital and labor are positive and statistically significant. Hence, the results from our model generally satisfy the regularity conditions imposed by economic theory.

We now plot the same estimates by region in Figures 4,5 and 6 in order to identify whether or not the sign and significance of the partial effects vary by different regions. We find that for the elasticity of physical capital, $\hat{\beta}_1$, more violations occur in the eastern and western regions than in the central region. Note, however, that the number of violations is relatively small in each region. We surmise that the (few) negative and significant elasticities probably occur because of insufficient skilled labor which leads to under-utilized physical capital. In general, our results show that both capital and labor positively and significantly increase output regardless of region.

4.2.2. Returns to Scale, Technical Change, and Input Bias

In terms of returns to scale, we can see from Figure 3 that a relatively small percentage of observations (15%) exhibit statistically significant increasing returns to scale technology. A larger fraction (54%) have statistically significant decreasing returns to scale, and 31% exhibit returns to scale that are not statistically distinguishable from constant returns to scale.

Figures 4,5 and 6 show that decreasing returns to scale is statistically significant for a substantial number of observations in each region, but occurs more frequently in the eastern and western regions (64% in the eastern region, 44% in the central region, 53% in the western region). Decreasing returns to scale is the sufficient condition for profit maximization, and indicates that firms may not benefit from expansion. We find some evidence that increasing returns to scale is statistically significant for some observations in each region, occurring more frequently in the central and western regions (7% in the eastern region, 19% in the central region, 20% in the western region). Constant returns to scale occurs most frequently in the central region (29% in the eastern region, 37% in the central region, 27% in the western region).

In addition, we expect that as China's economy becomes more competitive, returns to scale will converge to unity over time. We find that while we estimate decreasing returns to scale for most provinces, the evidence suggests that returns to scale may be converging to unity over time.

Specifically, we find that returns to scale for approximately 45% of eastern provinces appears to be converging to unity over time, 25% appear to be converging in the central region, and 20% appear to be converging in the western region.

Turning to technical change, $\partial \ln Y/\partial t$ in Figure 3, we find little evidence in favor of technical regress. We find a positive and significant technical change for 79% of our sample, 13% of the sample suggests technical regress, and 8% suggests neither progress nor regress. Thus for a majority of our sample, we find significant technical progress. At a provincial level, we find less evidence of technical regress in the central and western provinces (see Figures 5,6), while most of the negative and significant observations come from the eastern region (see Figure 4). We note, however, that there are still a substantial number of observations (45%) in the eastern region with significant technical progress.

We find substantial heterogeneity in input bias - the marginal effects of R&D and time on the elasticities of capital and labor - in the semiparametric model (see Stevenson [36] for a discussion on input bias). The marginal effect of time on the elasticities of labor is statistically different from zero in the fully parametric model, Model 2, which suggests that production technology is not input neutral.[6] In the semiparametric model, we find no evidence of input-neutrality at the mean and at each of the three quartile values of marginal effects. We find strong evidence in favor of capital-using technology at the 25th percentile (Q1), and labor-using technology at all the percentiles.

4.2.3. R&D Elasticity

We now turn to the productivity of R&D. For this we examine the elasticity $\partial \ln Y/\partial \ln Z_1$ where Z_1 is R&D. Figure 3 shows a plot of the productivity of R&D. We find that in general, R&D has a positive effect on output: the mean value of $\partial \ln Y/\partial \ln Z_1$ for Model 3 in Table 2 is 0.1531, which means that if R&D investments are increased by 1%, ceteris paribus, output would increase by 0.1531%. The effect of R&D on output is positive and statistically significant for 79% of the observations in the sample. This suggests that China may see increased productive efficiency by reallocating R&D investments to regions (or provinces) with positive and significant returns to R&D.

In order to identify in which regions R&D has the greatest impact on output, we turn to Figures 4,5 and 6. We find evidence of a positive and significant effect of R&D on output for 83% of the observations in the eastern region, 94% of the observations in the central region, and 63% of the observations in the western region. In terms of magnitude, the mean R&D impacts are 0.2202, 0.1637 and 0.0707 in the eastern, central, and western regions, respectively. Therefore, our results suggest that while there are positive effects of R&D in all regions of China, the magnitudes of such effects are different across regions.

In general, we find a positive and significant effect of R&D on output in the eastern region. In particular, the effect of R&D on output in Tianjin province is closest to that in Beijing, which has the largest R&D effect. This is because of the geographical proximity of Tianjin to Beijing and hence, recent economic development: as costs of land and labor rise in Beijing, Tianjin easily attracts resources from Beijing (e.g., capital, technology, and skilled labor) for lower production

[6] Technology is always input-neutral in Model 1 by construction.

costs. Hence, R&D investments exhibit a high return in Tianjin.

The elasticity of output with respect to R&D is insignificant for only two of the eleven eastern provinces (specifically, Guangdong and Zhejiang). The two eastern provinces with an insignificant effect of R&D on output suggests that even if a province has a well-established infrastructure, advanced science and technology, and sufficient skilled labor, higher R&D investments do not necessarily lead to higher productivity. This may be because of the fact that much of the technological innovation introduced in these two provinces of the eastern region is developed internationally and imported into China. There are many multinational corporations operating in the eastern region, and technological innovations are often directly introduced from company headquarters overseas instead of being developed locally by Chinese companies. Hence, the expected relationship between R&D and output in these provinces may not necessarily exist. Another possible explanation may be the diminishing marginal product of R&D, after controlling for time effects (see Marsili [37] and Mairesse and Mohnen [38]). It is likely that some provinces in the eastern region are fully utilizing their R&D capital, so that the marginal product of R&D is close to zero. Therefore, further investments in R&D may not always have a positive and significant impact on output. Hainan province, in particular, has a significantly negative relationship between R&D and output. Although Hainan province is geographically located in the southeastern part of China, it appears to be an outlier in the eastern region in that most of the investments are attracted by nearby provinces.[7]

We find the R&D elasticity is positive and significant in most of the central provinces over all time periods. This suggests that under current levels of production, science, and technology, the central region is not making full use of its R&D investments and the marginal product of R&D is greater than zero. Since most of the central provinces have the necessary prerequisites (e.g., infrastructure and human resources) for R&D investments to be effective, the marginal product of R&D is positive. While this suggests potentially large gains in productivity to be achieved from reallocating R&D investments to the central region, we note that the elasticity of R&D is insignificant in Heilongjiang province for many years, in particular.

We find that in three of the ten western provinces,[8] the elasticity of output with respect to R&D is significantly negative in most time periods. Since the western region is the most underdeveloped region in China, this may indicate that these provinces lack certain prerequisites for R&D to be effective. Descriptive statistics (see Table 1) show that the mean level of R&D investment is lowest in the western region. Without a sound manufacturing infrastructure, advanced science and technological abilities, and abundant skilled labor, R&D may not be able to positively influence productivity because it may either be potentially missallocated or not correctly used.[9] All the other seven western provinces benefit from a positive and significant effect of R&D.

Figure 7 reports the empirical cumulative distribution functions (ECDFs) of the R&D elasticity and technical change. To understand these plots, see that if the ECDF of the R&D elasticity for the western region lies below (to the left of) the ECDF of the R&D elasticity for the eastern

[7]In particular, Hainan province has greater investments in tourism than in the high technology industry.

[8]Specifically, Neimenggu, Shaanxi, and Ningxia.

[9]Negative R&D elasticities were also found in Li [19] who employed the DEA method to estimate the elasticity using data on thirty-two industries in China over the period 1996-2003.

region over a sufficiently large interval, then the R&D elasticity in the eastern region stochastically dominates the R&D elasticity in the western region. This means that the estimates from the eastern region are generally larger than those from the western region. This figure confirms that there is a substantial amount of heterogeneity across regions. The first panel (left) reports the ECDF of the R&D elasticity. It can be seen that the eastern region generally has a higher return to R&D than the central region, which in turn generally has a higher return to R&D than the western region. This confirms our previous discussion of positive and significant R&D effects in the eastern and central regions, and smaller or even negative R&D effects in the western region. The second panel (right) reports the ECDF of technical change. We can see that technical progress (i.e., positive technical change) more frequently occurs in the western region than in the central region, while in the eastern region sometimes technical regress (negative technical change) occurs. In addition, the eastern region generally has a smaller magnitude of technical progress than the central region.

These results indicate that while the eastern region benefits the most from R&D investments, it suffers the most from technical regress at the same time. While the western region benefits the least from R&D investments, it enjoys the most from technical progress. The implications regarding the central region are interesting: the central region benefits from R&D investments more than the western region and benefits from technical progress more than the eastern region. This suggests that R&D investments in the central region would be effective while technical progress may further consolidate the development of the central region.

Our results have direct implications for future investment and resource allocation in China. Because we find strong significance of R&D on productivity in the eastern and central regions, and significance of technical progress in the central and western regions, resources should be allocated accordingly between the regions to maximize their productivity. R&D investments should be focused in the eastern and central regions; the combination of R&D and technical progress in the central region potentially suggests that returns to R&D investments in this region may be very large. We point out, however, that there is still a positive and significant effect of R&D on productivity in certain provinces in the western region. Hence, it would not necessarily be efficient to abandon R&D investments in the western region for R&D investments in the central or eastern regions. Since the eastern region is more developed, we hypothesize that more advanced (e.g., scientific) research should continue to be done in the eastern region to take advantage of the established infrastructure, while R&D in manufacturing could potentially be moved to the central region.[10]

5. Conclusion

In this paper we focus on the effect of R&D on the productivity of the Chinese high technology industry across three major geographical regions in China. Due to large regional differences in China, we use a simple generalization of a Cobb-Douglas production function to incorporate parameter heterogeneity and flexibility into a standard production function framework. We model the

[10] Indeed, Foxconn International Holdings, one of the largest manufacturers of electronics and computer components worldwide, has recently begun relocating its factories to the central region of China, presumably to take advantage of the lower costs of labor in the central region.

elasticities of capital and labor as unknown functions of R&D, one of the environmental factors that may shift the production frontier for each region. We estimate both a semiparametric model and its parametric counterpart, and find that the semiparametric model yields more intuitive results and fewer economic violations while the parametric specification is rejected by a formal statistical goodness-of-fit test. The results from semiparametric model generally show positive and significant contributions of R&D on the productivity in China's high technology industry, with the mean R&D elasticity being 0.1531. As expected, we find that the overall impact of R&D on productivity varies substantially across regions and provinces. In particular, we find that the eastern and central regions have the largest returns on R&D investments, while the central and western regions enjoy the most technical progress. This suggest that a partial reallocation of R&D investments to the central region of China is reasonable since it benefits from R&D investments more than the western region and benefits from technical progress more than the eastern region. A possible future study may employ the empirical model presented in this paper as a foundation for the investigation of regional heterogeneity in China or other countries.

Technical Appendix

This appendix describes in further detail the semiparametric model used to estimate Model 3. Recent development of kernel methods allows one to smooth both continuous (i.e., $Z_{lit}\ \forall l = 1, \ldots, L$) and (discrete) categorical variables (i.e., μ_i) (see Racine and Li [39] and Li and Racine [40]). To simplify notation, we rewrite (8) as

$$\mathcal{Y}_{it} = \mathcal{X}'_{it}\Phi(Z_{it}) + u_{it}, \tag{13}$$

in which $\mathcal{Y}_{it}$ is the log of Y_{it}, $\mathcal{X}_{it}$ is a $(K+1)\times 1$ vector containing one and the log of the regressors in X_{it}, Z_{it} is an $(L+1)\times 1$ vector of environmental variables, and $\Phi(\cdot)$ is a vector of unknown coefficient functions to be estimated. Following Cai et al. [22] and Li and Racine [27], the local-linear least-squares estimator yields $\hat{\Phi}(z)$ and the first order gradient of $\hat{\Phi}(z)$ (i.e., $\partial\hat{\Phi}(z)/\partial z_l$). Letting $\hat{\gamma}(z) = (\hat{\Phi}(z), \partial\hat{\Phi}(z)/\partial z_l)$, we have

$$\hat{\gamma}(z) = \left[\sum_{i=1}^{N}\sum_{t=1}^{T}\mathcal{S}_{it}\mathcal{S}'_{it}K_h\left(Z_{it}, z\right)\right]^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathcal{S}_{it}\mathcal{Y}_{it}K_h\left(Z_{it}, z\right) \tag{14}$$

in which N denotes the total number of industries, T denotes the time period, h is an $L+1$ dimensioned vector of bandwidths, and $K(\cdot)$ is a generalized product kernel function. Let Z^c_{it} be an L-vector of continuous variables only (i.e., $Z^c_{it} = (Z_{1it}, \ldots, Z_{Lit})$), then

$$\mathcal{S}_{it} = \begin{pmatrix} \mathcal{X}_{it} \\ \mathcal{X}_{it}\bigotimes(Z^c_{it} - z^c) \end{pmatrix}, \tag{15}$$

in which $\bigotimes$ denotes the Kronecker product. Let Z^u_{it} be the unordered categorical variable, or fixed industry effects (i.e., $Z^u_{it} = \mu_i$),[11] thus $Z_{it} = (Z^c_{it}, Z^u_{it})$. We can then define the kernel function as

$$K_h(Z_{it}, z) = K^u(Z^u_{it}, z^u, h^u)\prod_{l=1}^{L}K\left(\frac{Z_{lit} - z_l}{h_l}\right), \tag{16}$$

in which h^u denotes the bandwidth for the unordered categorical variable, and h_l denotes the bandwidth for the l-th continuous variable. Following Aitchison and Aitken [41], and letting c denote the number of categories the discrete variable can take,

$$K^u(\cdot) = \begin{cases} 1 - h^u, & \text{if } Z^u_{it} = z^u \\ h^u/(c-1), & \text{otherwise} \end{cases} \tag{17}$$

and

$$K(\cdot) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\frac{Z_{lit} - z_l}{h_l}\right)^2\right). \tag{18}$$

[11] Kernel methods also allow for ordered categorical variables (e.g. time). We treat time as continuous in our model since technical change can be most easily captured by a time trend variable whose derivatives are well-defined. We note that using an ordered categorical variable to control for time yields qualitatively consistent results to those reported here.

We select the vector of bandwidths, h, using least-squares cross-validation. The cross-validation criterion function is given by:

$$CV_{ll}(h) = \min_{h} \sum_{i=1}^{N} \sum_{t=1}^{T} [\mathcal{Y}_i - \mathcal{X}_{it}' \hat{\Phi}(Z_{it})_{-it}]^2, \tag{19}$$

in which $\mathcal{X}_{it}' \hat{\Phi}(Z_{it})_{-it}$ is the leave-one-out estimator of the conditional mean. The advantage of using least-squares cross-validation to select the bandwidths is that it allows us to avoid any potential pitfalls associated with an ad hoc choice of bandwidth. See Li and Racine [27] for details.

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Table 1: **Summary Statistics of the Variables**

Variable		Mean	Sd.	Min.	Max.
Log of Output ($\ln Y$)	Total obs.	4.2713	1.5111	-0.2614	7.8262
	Eastern	5.440	1.3280	1.797	7.826
	Central	4.018	0.6018	2.630	5.553
	Western	3.1880	1.2973	-0.2614	5.8237
Log of Capital ($\ln X_1$)	Total obs.	4.0304	1.3091	0.8419	7.1989
	Eastern	4.848	1.2296	1.489	7.199
	Central	4.066	0.7808	2.160	5.326
	Western	3.1026	1.1146	0.8419	5.2076
Log of Labor ($\ln X_2$)	Total obs.	11.362	1.3280	7.948	14.845
	Eastern	12.21	1.3253	8.74	14.84
	Central	11.30	0.3587	10.60	12.02
	Western	10.474	1.2294	7.948	12.419
Log of R&D ($\ln Z_1$)	Total obs.	11.083	2.0751	5.388	15.565
	Eastern	12.401	1.7941	6.782	15.565
	Central	10.89	1.0302	8.62	12.67
	Western	9.791	2.1310	5.388	13.511

1. The sample consists of 232 observations spanning 29 provinces over 8 years (2000-2007).
2. There are 88 observations for the eastern region, 64 observations for the central region, and 80 observations for the western region.
3. Output, capital, labor, and R&D are measured in thousands RMB (Chinese currency).

Table 2: **Summary of Results for Models 1-3**

	$\hat{\beta}_1$	$\hat{\beta}_2$	RTS	$\partial \ln Y/\partial \ln Z_1$	$\partial \ln Y/\partial t$	$\partial\hat{\beta}_1/\partial \ln Z_1$	$\partial\hat{\beta}_1/\partial t$	$\partial\hat{\beta}_2/\partial \ln Z_1$	$\partial\hat{\beta}_2/\partial t$
Model 1	0.1241	0.5046	0.6287	0.0388	0.1038	-	-	-	-
	(0.0386)	(0.0551)	(0.0583)	(0.0363)	(0.0112)				
Model 2									
Mean	0.1617	0.5552	0.7168	0.0004	0.1074	-0.1063	0.0324	0.0561	-0.0775
	(0.0266)	(0.0744)	(0.0865)	(0.0054)	(0.0082)	(0.0646)	(0.0206)	(0.0769)	(0.0263)
Q1	-0.0515	-0.1110	0.0877	-0.0601	0.0635	-	-	-	-
	(0.0182)	(0.0306)	(0.0481)	(0.0054)	(0.0022)				
Q2	0.1536	0.6106	0.6999	-0.0049	0.1022	-	-	-	-
	(0.0140)	(0.0482)	(0.0425)	(0.0049)	(0.0033)				
Q3	0.3486	1.0569	1.4669	0.0544	0.1376	-	-	-	-
	(0.0296)	(0.1715)	(0.2082)	(0.0041)	(0.0354)				
Model 3									
Mean	0.2755	0.6572	0.9327	0.1531	0.0544	0.0206	0.0070	0.0145	-0.0366
	(0.0232)	(0.0439)	(0.0633)	(0.0150)	(0.0061)	(0.0047)	(0.0028)	(0.0054)	(0.0037)
Q1	0.1620	0.5253	0.8529	0.0691	0.0192	-0.0186	-0.0206	-0.0348	-0.0592
	(0.0082)	(0.0059)	(0.0067)	(0.0050)	(0.0029)	(0.0029)	(0.0031)	(0.0034)	(0.0047)
Q2	0.2636	0.6618	0.9123	0.1588	0.0438	0.0165	0.0014	0.0303	-0.0317
	(0.0129)	(0.0147)	(0.0066)	(0.0081)	(0.0019)	(0.0029)	(0.0016)	(0.0042)	(0.0019)
Q3	0.3917	0.7914	0.9997	0.2474	0.0891	0.0560	0.0262	0.0666	-0.0071
	(0.0648)	(0.3048)	(0.6383)	(0.0191)	(0.0119)	(0.0048)	(0.0017)	(0.0069)	(0.0017)

1. The numbers in the parentheses are standard errors.
2. $\partial \ln Y/\partial \ln Z_1$ is an elasticity.
3. Each model includes provincial level fixed effects.
4. The null of equality of distributions across Models 2 and 3 for $\hat{\beta}_1$, $\hat{\beta}_2$, RTS, $\partial \ln Y/\partial \ln Z_1$, $\partial \ln Y/\partial t$, respectively, is rejected at the 1% level.

Table 3: **Bandwidths and Percentage of Violations**

Z Variable	$R\&D$	t	$Province$
Bandwidth	1.9823	2.7810	0.2489
$2 \times \sigma_z$	4.1502	4.5925	-
$\mathcal{X}$ Variable	Intercept	$Capital$	$Labor$
Coefficient	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$
Percentage of violations: Semiparametric	-	12%	0%
Percentage of violations: Parametric	-	27%	28%

1. Both $R\&D$ and t are continuous, $Province$ is an unordered categorical variable in the semiparametric model and dummy variables in the parametric model.
2. Bandwidths are selected via least-squares cross-validation.
3. σ_z denotes standard deviations of continuous Z variables.
4. Model specification test proposed by Cai et al. [22] rejects the parametric model with a zero empirical p-value from 399 wild bootstrap replications.

Figure 1: **Regional Map of China**

Figure 2: **A Single Input Production Function.**

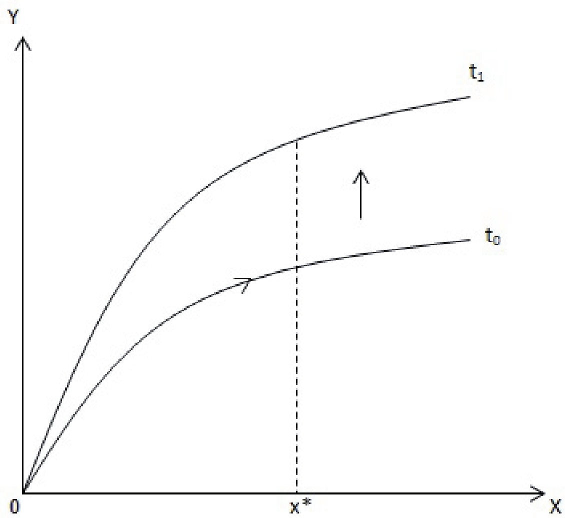

Figure 3: **Estimates and Confidence Intervals: Full Sample**

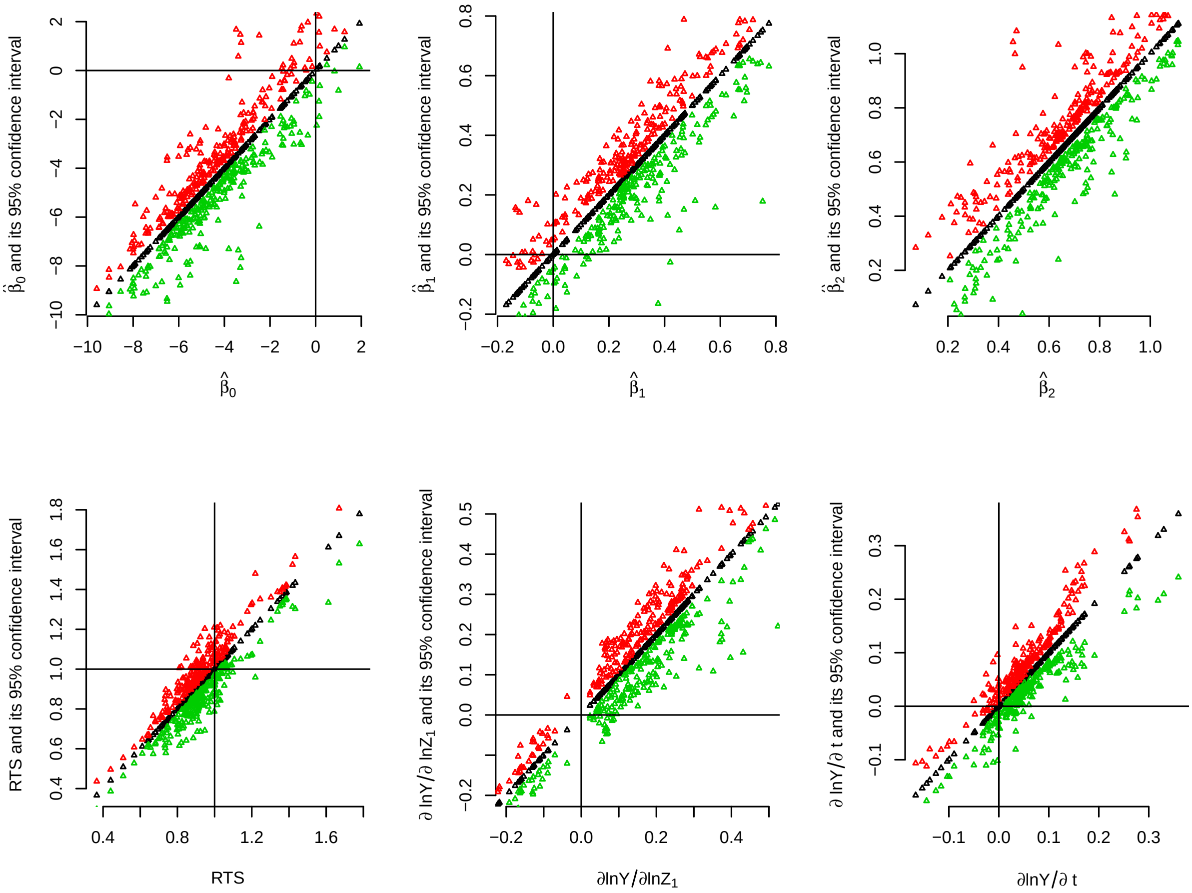

Figure 4: **Estimates and Confidence Intervals: Eastern Region**

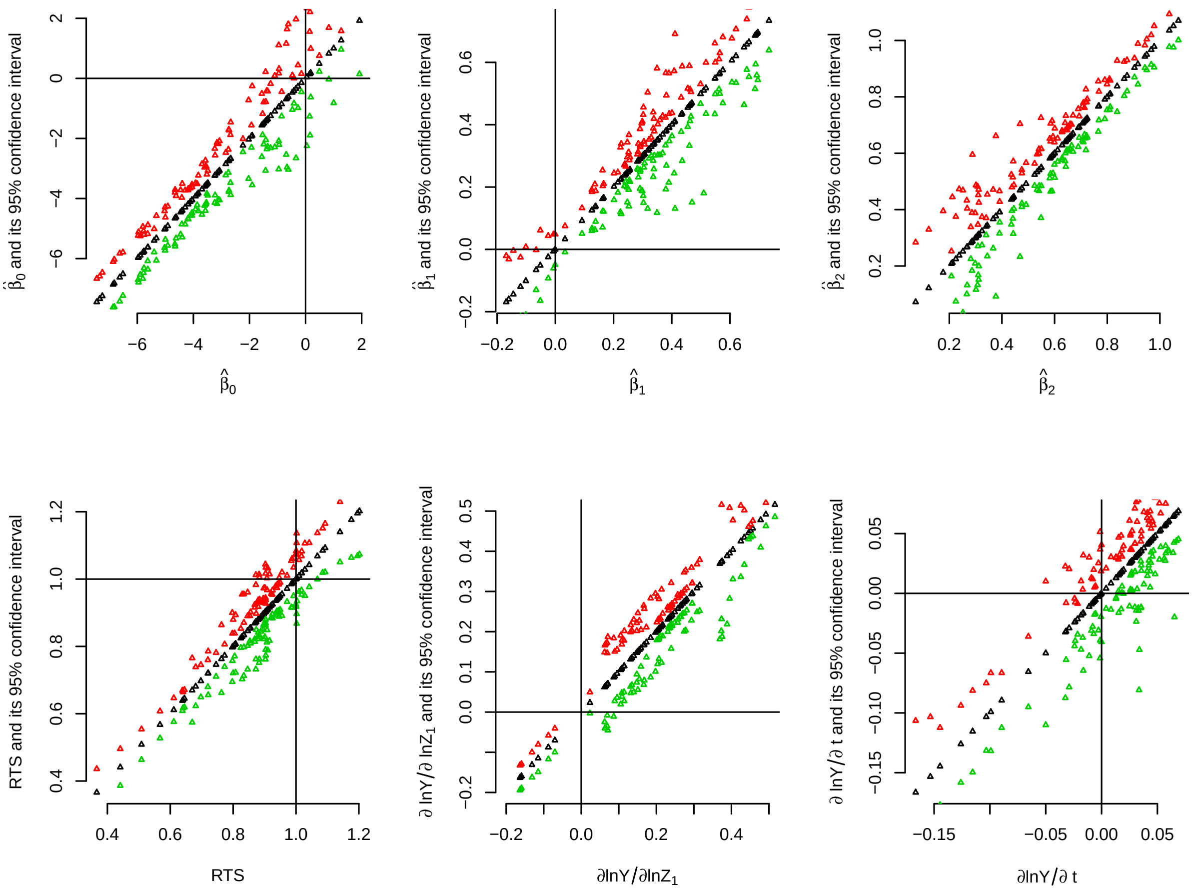

Figure 5: **Estimates and Confidence Intervals: Central Region**

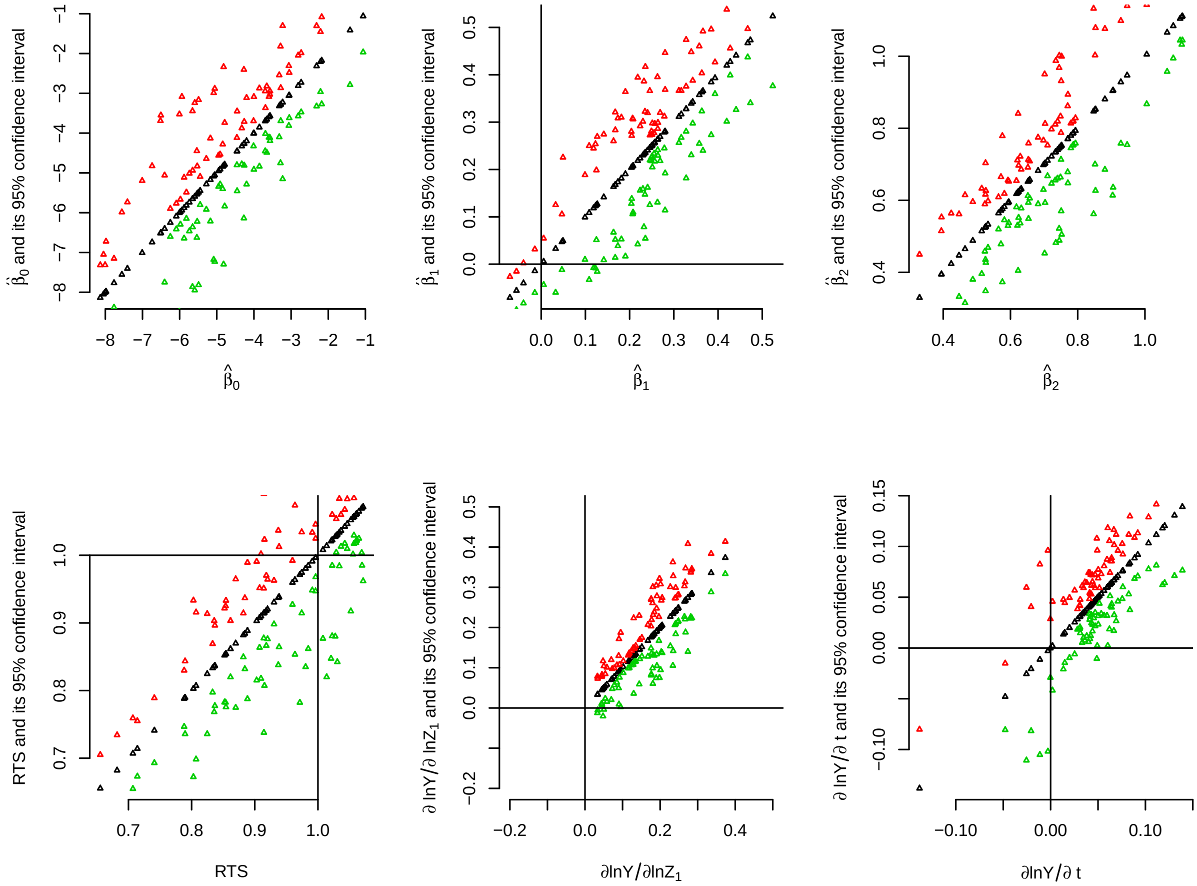

Figure 6: **Estimates and Confidence Intervals: Western Region**

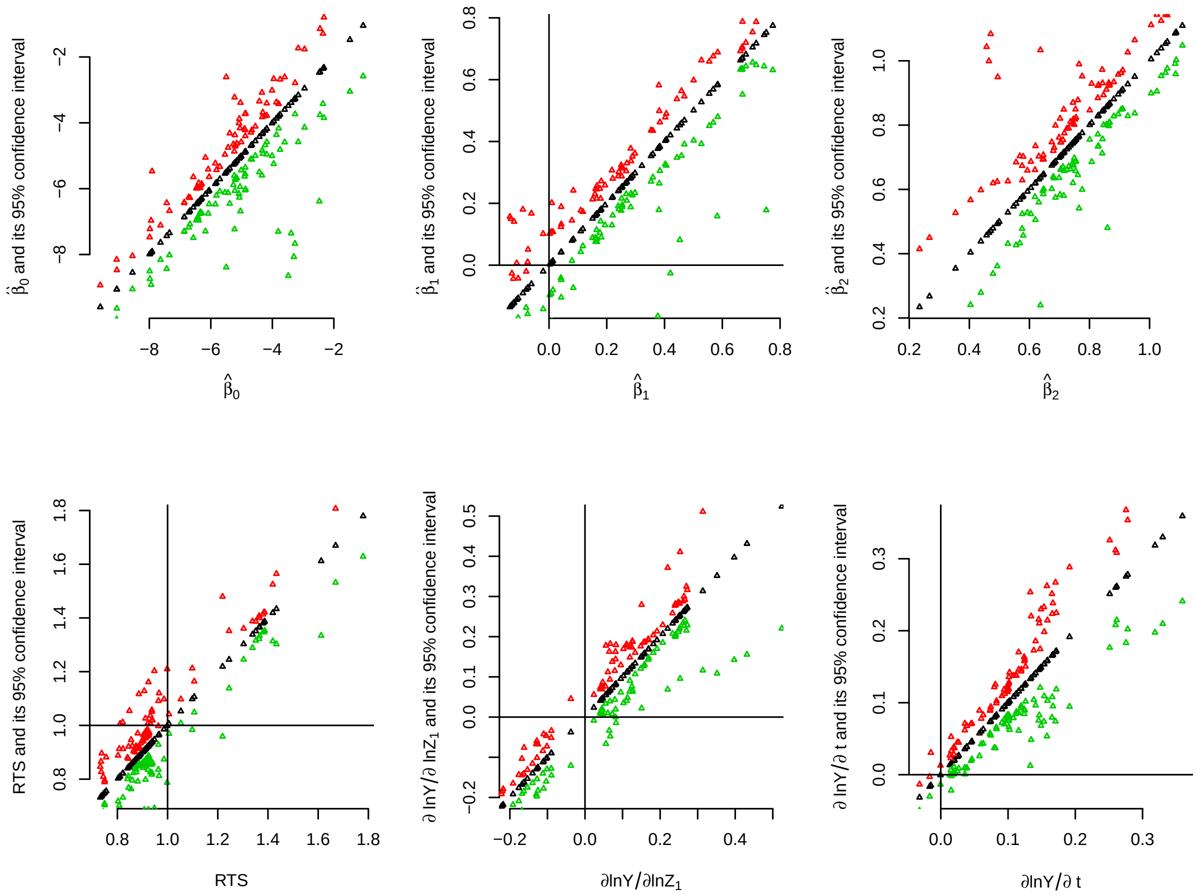

Figure 7: **Regional Analysis: R&D Elasticity and Technical Change**