Labour-Use Efficiency in China:
A Stochastic Frontier Analysis

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Abstract

Using panel data and applying the stochastic frontier analysis, this paper investigates the labor-use efficiency of 24 provinces/administrative regions of China between 2011 and 2019. The average labor efficiency relative to the most efficient province was 86.1 per cent, whereas Tianjin, followed by Shanghai, was the most efficient province (100 per cent and 95.2 per cent, respectively). We find a potential for reducing labor demand by up to 13.9 per cent across all provinces. At the same time, Guangdong is the least efficient province and could improve its labor efficiency by about 19.5 per cent. In addition, the paper studies labor elasticity and marginal risk with respect to output, capital, wage, and time.

Keywords: *labor, efficiency, China, elasticity of labor demand, marginal risk effect, labor requirement frontier*

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1.   Introduction

With an average annual growth rate of 9.4 per cent, China's economy grew 13.5 times from 1989 to 2019 (Wu et al., 2022). This rapid growth of China's economy over the past three decades is mainly attributed to the abundant labor supply rather than labor-use efficiency (Cheng et al., 2020), which is reflected in an average labor efficiency of only about 54 per cent in the year 2016 across provinces of China (Liu, 2019). However, China faces a deteriorating labor supply due to the recent falling birth rate and the fastest-growing aging population (Textor, 2022a). For instance, China's proportion of employed people to the whole population experienced an annual average decrease of about 0.46 per cent between 2011 and 2021 (Textor, 2022b). Therefore, China's transition from a labor-intensive to an economy that is efficient in labor use is essential to overcome the 'middle-income trap' and transform its economic growth (Cheng et al., 2020). This also implies that analyzing the labor-use efficiency across China is desirable for policy considerations.

The labor-use efficiency is measured by the distance of the quantity of labor used from the labor demand frontier, and the labor demand frontier is defined as the minimum (optimal) quantity of labor required to produce a given output level (Heshmati, 2001; Kumbhakar and Hjalmarsson, 1995, 1998). There are two approaches to estimating labor use efficiency: a non-parametric method - data envelopment analysis (DEA) and a parametric method - stochastic frontier analysis (SFA). Although the DEA model does not impose constraints on function forms and weights, which would otherwise require proportionate improvements of all inputs or outputs Cheng et al. (2020), the present study employs the SFA approach since following Kumbhakar and Hjalmarsson (1995): (1) the notion of the frontier is in line with the fundamental economic theory of optimization; (2) distance from a frontier is interpreted as a measure of an economic unit's efficiency in pursuing its behavioral or technical objectives; (3) understanding the structure of the frontier and the relative efficiency of economic units provides us with many policy applications.

Using SFA in balanced panel data, we investigate the labor-use efficiency of 24 provincial-level administrative regions of China, referred to as provinces, from 2011 to 2019. We use a flexible translog function to specify the labor demand. The labor demand is a function of output (real GDP), average wage, capital stock, province-specific variables that

capture the characteristics of the technology and production environment (including foreign direct investment, government expenditure, and research and development), and time variables. The variance function, which accommodates marginal effects, enters multiplicatively with the demand function. The variance function allows for a specific form of heteroscedasticity in the labor demand function (Heshmati, 2001). This paper specifies the variance function as a function of output produced, wage, capital stock, and time effect. The parameters of the demand and variance models are estimated through a multi-step procedure using generalized least squares (GLS) and a nonlinear method, respectively. Besides the labor-use efficiency, we also compute the elasticity of labor demand and marginal risk effects with respect to output, wage, and capital. Finally, it is noteworthy that, for each year, the labor-use efficiency is measured relative to the province with the best labor-use practice in our sample, which is assumed to be 100 per cent efficient.

To our knowledge, three other studies investigate labor-use efficiency in China. However, each of these studies has notable differences from the current study. First, Kumbhakar and Zhang (2013) investigate labor-use efficiency across China's manufacturing industry, while our paper investigates labor-use efficiency across China's provinces. Therefore, by investigating labor-use efficiency on a provincial level, the present study bears different policy implications. Second, Liu (2019) examines labor-use efficiency across 22 provinces of China in 2016. In contrast, the present study spans nine years, which allows us to capture the dynamic labor-use efficiency. Finally, Cheng et al. (2020) studied labor-use efficiency across 23 provinces of China from 2007 to 2017 using the DEA model. Conversely, the present study employs the SFA approach due to its abovementioned advantages. Moreover, the biggest difference between our study and the existing literature is that we employ the variance function to generalize the labor demand function to capture risks that directly affect provinces' production. Since we employ the labor requirement function approach, the production risk is interpreted as labor variance (Heshmati, 2001). It is labeled as variance since both the mean and variance of labor respond to different combinations of production. A non-optimal labor level with high deviation significantly affects the productivity of provinces when the deviation does not correspond to demands in the event of shocks, for example, the COVID-19 pandemic.

In the following, section 2 discusses the relevant literature on labor-use efficiency in China, section 3 presents the theoretical model, section 4 reports the data sources and variable measurements, section 5 lays out the empirical model and estimation strategy, section 6 reports and discusses the results and section 7 concludes.

2.   Literature Review on Labor-use Efficiency in China

As mentioned above, three studies that investigate labor-use efficiency in the context of China include Kumbhakar and Zhang (2013), Liu (2019), and Cheng et al. (2020). First, Kumbhakar and Zhang (2013) investigate the labor-use efficiency and employment elasticity of China's manufacturing sector using panel data from 28 industries between 1999 and 2008. An industry that uses more labor than the minimum required to produce a given output is considered inefficient. The study uses SFA, where the optimal level of labor is defined as a function of output produced, technology proxied by a time trend, capital inventory, a vector of variables that capture the attributes of the industry's production technology and environment, including a dummy capturing if the industry is monopolistic and a dummy that captures labor-intensive industries. The results yield an average labor-use efficiency rate of 85.5 per cent across industries, with the least and most efficient industries being 32.9 per cent and 100 per cent efficient, respectively. Thus, the study concludes that labor is overused by 14.5 per cent. The mean employment elasticity with respect to output is 0.80, implying that a 1% increase in output requires a 0.80 per cent increase in labor use.

Second, employing the DEA and SFA models, Liu (2019) studies the labor efficiency of 22 provinces, 5 autonomous regions, and 4 municipalities in China in 2016. It is considered a province uses more labor than the minimum required to produce a certain level of output as inefficient. Liu (2019) uses provincial capital stock and employment as input variables and gross national product as output. The provincial labor-use efficiency ranking calculated by the two methods is mostly similar, with Beijing and Shanghai being the first and second most efficient and Guangxi and Yunnan being the least efficient provinces. The least efficient provinces are generally concentrated in the northwest region of China, and the most efficient cities are the eastern coastal cities. Furthermore, the study finds that some central region cities rank lower than the northwest region, which reflects an inconsistency with their economic development level. For instance, they find

that Henan, while ranking fifth in total GDP contribution in China, is ranked 27th in efficiency. They infer that the high population of the province may be the cause of this inefficiency in labor use.

Finally, employing the DEA model, Cheng et al. (2020) investigate the humanitarian labor efficiency and labor-use efficiency across 23 provinces of China from 2007 to 2017. Generally, labor-use efficiency has a downward trend in the long run but fluctuates in the short run. From 2007 to 2011, the average labor efficiency was above 0.7 per cent; after 2014, it fell to 0.55 per cent. The sub-regional estimation of labor-use efficiency shows that the western regions are the least efficient across this period, while the central regions are the most efficient. Since the study focuses more on humanitarian labor efficiency, it does not report labor-use efficiency on the provincial level.

3.   Theoretical Model

3.1   Labor Demand Function

Theoretically, an economic unit is considered inefficient in two cases: (1) its output levels produced are lower than the maximum permitted by its technology, (2) its input levels used are more than the minimum required by its technology to produce a given output quantity, thereby meaning that inputs are overused. In this paper, we follow the second case. We also assume that labor is the only variable input (i.e., all other inputs are quasi-fixed). Hence, a province is not efficient when it uses more labor than the optimal amount of labor required to produce a given output level (Y).

Let the desired labor level (L_{it}^*) be defined as the optimal amount of labor required to produce the given output level Y_{it} for province i at time t. This optimal level of labor is defined by the labor requirement frontier, which is specified as

$$L_{it}^* = f(Y_{it}, K_{it}, W_{it}, Z_{it}, t) \qquad (3.1)$$

where $f(.)$ represents the production technology, the subscript i represents the province i, and t represents the time. Y_{it} is the output, K_{it} is the capital stock, W_{it} is the wage, t indicates the exogenous rate of technical change represented by time trend or time dummy variables, Z_{it} consists of province-specific variables that capture the characteristics of the technology and

production environment that would affect the labor inefficiency and risk (or variance) of employment. According to Layard and Nickell (1986) and Kumbhakar and Zhang (2013), Z_{it} can be GDP growth, export, government expenditure, saving, domestic credit to the private sector, foreign direct investment, industry value added, R&D investment, and human capital.

Given K, W, and Z variables, if the province i at time t does not achieve the labor requirement frontier in producing Y_{it}, it is inefficient as there is excessive use of labor compared to the technically required amount. The relationship between the actual amount of labor used and the labor requirement frontier is modeled by Kumbhakar and Hjalmarsson (1995) as follows:

$$L_{it} = L_{it}^* e^{\tau_{it}}$$
(3.2)

where L_{it} is the actual quantity of labor used by province i at time t, and $\tau_{it} \geq 0$ for $\forall i$ and t. $\tau_{it} > 0$ represents technical inefficiency, measuring the percentage of labor overuse compared to the optimal level of labor required to produce the output vector Y_{it}. If $\tau_{it} = 0$, province i is technically efficient in labor use. Thus,

$$L_{it}^*/L_{it} = e^{-\tau_{it}}$$
(3.3)

is used to capture labor-use efficiency. The value of this ratio varies between 0 and 1 for $\forall i$ and t. Then, given the output Y_{it}, a province's labor demand is determined by: (i) the production technology f(.), (ii) technical inefficiency τ_it, and (iii) external factors to the province's control, such as global economic crisis, international conflicts, and trade barriers. These external factors are captured by the random term ϑ_{it} ($-\infty < \vartheta_{it} < \infty$), which is appended in the same manner as τ_{it} in equation (3.2). Thus, the labor requirement function in equation (3.2) can be written as

$$L_{it} = L_{it}^* e^{\tau_{it} + \vartheta_{it}} = L_{it}^* e^{\varepsilon_{it}}$$
(3.4)

where $\varepsilon_{it} = \tau_{it} + \vartheta_{it}$, is the error term. Due to the presence of ϑ_{it}, the labor requirement frontier function is stochastic.

Concerning the behavior of τ_{it}, following Battese and Coelli (1988), Kumbhakar (1988), and Heshmati (2001), we assume that τ_{it} is time-

invariant, i.e. $\tau_{it} = \mu_i \forall t$. Thus, the error term in equation (4) is restructured as

$$\varepsilon_{it} = \mu_i + \vartheta_{it} \tag{3.5}$$

μ_i is a persistent province-specific labor-use inefficiency, which is allowed to be correlated with the regressors. While no further assumptions are made on the distribution of μ_i, ϑ_{it} is assumed to have i.i.d $N(0,1)$.

The model in equation (3.4) is specified without regard for risk. Therefore, we employ the variance function to incorporate production risk. Since the approach used is the labor requirement function, the production risk is interpreted as labor variance (Heshmati, 2001) and specified as a function of all dispersion factors.

3.2 *Incorporating Variance Function*

To incorporate risk, we rewrite (3.4) as

$$L_{it} = f(X_{it}; \alpha) \exp(g(X_{it}; \beta)\varepsilon_{it}) \tag{3.6}$$

where $X_{it} = (Y_{it}, K_{it}, W_{it}, Z_{it}, t)$, $f(X_{it}; \alpha)$ is the demand part and $g(X_{it}; \beta)\,\varepsilon_{it}$ is the variance component. Equation (3.6) can be written in a logarithmic form as

$$lnL_{it} = lnf(X_{it}; \alpha) + g(X_{it}; \beta)\varepsilon_{it} \tag{3.7}$$

The expected value of L_{it}, $E(L)$ and its variance, $V(L)$, are

$$E(L) = f(X; \alpha)\exp(g^2(.)/2) \tag{3.8}$$

and

$$V(L) = f^2(.)\exp(g^2(.))[\exp(g^2(.)/2) - 1] \tag{3.9}$$

Thus, if $E(L) \geq f(X; \alpha)$, marginal variance (risk) effect with respect to $X_j(Y_{it}, K_{it}, W_{it}, Z_{it}, t)$ is

$$ME_j = \frac{\delta V(L)}{\delta X_j} = 2f(.) \exp\left(\frac{g^2(.)}{2}\right)$$
$$\times [f_j(.)\{\exp(g^2(.)) - 1\}$$
$$+ f(.)g(.)g_j(.)\{2\exp(g^2(.)) - 1\}]$$

(3.10)

where $fj(.)$ and $gj(.)$ are partial derivatives of $f(.)$ and $g(.)$ with respect to $X_j(Y_{it}, K_{it}, W_{it}, Z_{it}, t)$. The ME_j can be positive or negative depending on the sign and size of the $g(.)$ $gj(.)$. If $g(.)$ $gj(.) > 0$, $ME_j 0$ is positive. If $g(.)$ $gj(.) < 0$ and the absolute value of the second term in [.] is greater than that of the first term in [.], $ME_j 0$ is negative.

4.   Data

We obtain the data for our empirical analysis from the National Bureau of Statistics of China. The panel is balanced and consists of 24 provincial-level administrative regions (provinces) of China for nine years from 2011 to 2019. The total number of observations used is 216.

In this paper, the labor-use model is defined as an input requirement function where labor (L) is a function of output produced (Y), capital stock (K), wage (W), and province-specific variables that capture the characteristics of the technology and production environment (Z). Labor (L) is measured in the total quantity of employed people. Output (Y) is measured as the gross domestic product (GDP). Capital stock (K) is measured as the total investment in fixed assets. Wage (W) is measured as the average wage of employees. Province-specific variables that capture the characteristics of the technology and production environment (Z) consist of province government expenditure (GEX) and research and development ($R\&D$) proxied by the province's number of R&D projects in industrial enterprises. The GDP, total investment in fixed assets, average wage, and provincial government expenditure are given in the current Renminbi (RMB). They are transformed to fixed 2010 prices based on the consumer price index. Additionally, time dummies are used in the demand function to capture the exogenous rate of technical change, while a time trend is included in the variance function to represent the shifts in labor variance over time.

The summary statistics for all variables of our interest are reported in Table 1.

Table 1. Summary Statics

Variable	Mean	Std. Dev	Min	Max
Labor (thousand)	4538.7	3216.7	436.0	18493.0
GDP (billion RMB)	2702.9	1993.9	481.7	10798.7
Capital (billion RMB)	1974.9	1276.2	396.6	5907.4
Average Wage (thousand RMB)	62.21	22.79	31.30	166.80
Research and Development (number of projects)	1469.2	1908.7	128.0	10634.0
Province Government Expenditure (billion RMB)	529.0	253.3	179.1	1729.8

5. Empirical Model and Estimation Strategy

No assumption on functional form for $f(.)$ and $g(.)$ is made yet. Following the previous studies of the frontier production function (Haouas et al., 2003; Heshmati, 2001; Kumbhakar et al., 2002; Kumbhakar and Hjalmarsson, 1995; Kumbhakar and Zhang, 2013; Rashidghalam, 2017; Saggay and Raies, 2018), we approximate $f(.)$ by a translog function to place minimum restrictions on technology. Following Kumbhakar (1993) and Heshmati (2001), we adopt the linear form of $g(.)$. Using the translog function on $f(.)$ and the linear form of $g(.)$, the relationship in equation (3.6) becomes

$$lnL_{it} = \alpha_0 + \alpha_y lnY_{it} + \alpha_k lnK_{it} + \alpha_w lnW_{it} + \theta_t$$
$$+ \frac{1}{2} \big[\alpha_{yy}(lnY_{it})^2 + \alpha_{kk}(lnK_{it})^2 + \alpha_{ww}(lnW_{it})^2 \big]$$
$$+ \alpha_{yk} lnY_{it} lnK_{it} + \alpha_{yw} lnY_{it} lnW_{it} + \alpha_{kw} lnK_{it} lnW_{it} \text{ (3.11)}$$
$$+ \eta_1 lnGEX_{it} + \eta_2 lnR\&D_{it}$$
$$+ \big[\beta_y Y_{it} + \beta_k K_{it} + \beta_w W_{it} + \beta_t t \big](\mu_i + \vartheta_{it})$$

where L_{it}, Y_{it}, K_{it}, W_{it}, GEX_{it}, and $R\&D_{it}$ are defined above, subscripts i and t denote province and time, respectively. Here, θ_t is a vector of time dummy variables capturing the exogenous rate of technological change. The exogenous rate of technical change can be captured by time trends or time dummy variables. In the time trend model, however, technical change is assumed to be a smooth, continuous, and monotonous process, while in the dummy model, it is assumed to be a discontinuous and non-monotonous process (Heshmati, 2001). Thus, the time dummy model is more appropriate

for our panel data. Due to the small sample size, we do not include any interactions between time dummies and other explanatory variables to save degrees of freedom.

Time trend, t, is used in the variance component to capture the shifts in the variance over time. The shifts in the variance affect output produced, labor demand, and the levels of inefficiency. The effect of technical inefficiency on labor demand is captured by $g(Y_{it}, K_{it}, W_{it}, t; \beta)\mu_i$. Hence, while μi is time-invariant, its effect on labor demand may vary with time. Here, μ_i and θ_t are treated as fixed, which implies that we are working with a fixed effects model.

In the labor requirement function, there might be an endogeneity problem because output Y and capital stock K are determined by labor L. To deal with this problem, we regress output Y and capital stock K on exogenous variables in the model and use their predicted values in equation (3.11).

Following Just and Pope (1978), Kumbhakar (1993), and Heshmati (2001), we estimate equation (3.11) through the following process:

Step 1: We use ordinary least squares (OLS) to estimate equation (3.11) without regard to the variance function $g(.)$. μ_i is estimated from 23 provincial dummies and θ_t are estimated from eight time dummies. Since the error term (ϑ_{it}) has a mean of zero, the OLS estimators are unbiased and consistent. However, due to the omission of the variance function, the error term is heteroscedastic; thus, the OLS estimators here are inefficient.

Step 2: Using α, μ, and θ estimated in step 1, we calculate the residuals as follows:

$$\hat{\varepsilon}_{it} = \ln L_{it} - \Big(\alpha_0 + \alpha_y lnY_{it} + \alpha_k lnK_{it} + \alpha_w lnW_{it} + \theta_t T$$

$$+ \frac{1}{2}\big[\alpha_{yy}(lnY_{it})^2 + \alpha_{kk}(lnK_{it})^2 + \alpha_{ww}(lnW_{it})^2\big]$$

$$+ \alpha_{yk} lnY_{it} lnK_{it} + \alpha_{yw} lnY_{it} lnW_{it} + \alpha_{kw} lnK_{it} lnW_{it}$$

$$+ \eta_1 lnGEX_{it} + \eta_2 lnR\&D_{it} + \mu_i\Big) \tag{3.12}$$

From (3.11) and (3.12), we know that:

$$\hat{\varepsilon}_{it} = \big[\beta_y Y_{it} + \beta_k K_{it} + \beta_w W_{it} + \beta_t t\big]\vartheta_{it} \tag{3.13}$$

In logarithmic terms, equation (3.13) is written as:

$$ln\hat{\varepsilon}_{it} = ln[\beta_y Y_{it} + \beta_k K_{it} + \beta_w W_{it} + \beta_t t] + ln\vartheta_{it} \qquad (3.14)$$

Multiplying both sides of (3.14) by 2, we get:

$$2ln\hat{\varepsilon}_{it} = 2ln[\beta_y Y_{it} + \beta_k K_{it} + \beta_w W_{it} + \beta_t t] + 2ln\vartheta_{it}$$

$$ln\hat{\varepsilon}_{it}^2 = ln[\beta_y Y_{it} + \beta_k K_{it} + \beta_w W_{it} + \beta_t t]^2 + ln\vartheta_{it}^2 \qquad (3.15)$$

Since ϑ_{it} is assumed to be i.i.d $N(0,1)$, $ln\vartheta_{it}^2$ is the logarithm of aχ^2 variable with one degree of freedom. Following Theorem 2 of Just and Pope (1978), the estimates of $ln\vartheta_{it}^2$ have a mean and variance of -1.2704 and 4.9348, respectively. These specifications are employed in estimating equation (3.13).

We rewrite (3.15) as:

$$ln\hat{\varepsilon}_{it}^2 = -1.2704 + ln[\beta_y Y_{it} + \beta_k K_{it} + \beta_w W_{it} + \beta_t t]^2 + ln\vartheta_{it}^2 + 1.2704 \ (3.16)$$

Let $\vartheta_{it}^* = ln\vartheta_{it}^2 + 1.2704 \rightarrow E(\vartheta_{it}^*) = 0 \ and \ V(\vartheta_{it}^*) = 4.9348$. Then, (3.16) becomes:

$$ln\hat{\varepsilon}_{it}^2 = -1.2704 + ln[\beta_y Y_{it} + \beta_k K_{it} + \beta_w W_{it} + \beta_t t]^2 + \vartheta_{it}^* \qquad (3.17)$$

We estimate (3.17) using the nonlinear least squares by the linearization method to obtain the estimates of β.

Step 3: Using the estimates of μ_i obtained in step 1, we re-estimate equation (3.11) using GLS to get asymptotically efficient estimates of α and β (Note that the same results can be obtained by using OLS after dividing both sides of (11) by $\hat{g}(.) = \hat{\beta}_y Y_{it} + \hat{\beta}_k K_{it} + \hat{\beta}_w W_{it} + \hat{\beta}_t t$).

Step 4: We iteratively repeat steps 1 to 3 until convergence, where changes in the estimates of α, β, and the value of the labor requirement function are negligible.

Step 5: Since we estimate μ_i from province dummies, the μ for the reference province cannot be estimated. Thus, labor-use inefficiency is measured relative to the most efficient province each year in our sample, with an assumption that $\mu = 0$ (fully efficient) for the most efficient province. The labor-use inefficiency is calculated as

$$LINEFF_{it} = g(X_{it}; \hat{\beta})(\alpha_0 + \mu_i) - \min_t[g(X_{it}; \hat{\beta})(\alpha_0 + \mu_i)] \qquad (3.18)$$

and labor-use efficiency as

$$LEFF_{it} = \exp(-LINEFF_{it}) \qquad (3.19)$$

which is both province- and time-specific.

Next, the elasticities of labor demand with respect to output, capital stock, and wage need to be calculated at all data points for making an economic inference, where E_y represents the return to scale.

$$E_y = \frac{\partial \ln L_{it}}{\partial \ln Y_{it}} = \alpha_y + \alpha_{yy} \ln Y_{it} + \alpha_{yk} lnK_{it} + \alpha_{yw} \ln W_{it} \qquad (3.20)$$

$$E_k = \frac{\partial \ln L_{it}}{\partial \ln K_{it}} = \alpha_k + \alpha_{kk} \ln K_{it} + \alpha_{yk} lnY_{it} + \alpha_{kw} \ln W_{it} \qquad (3.21)$$

$$E_w = \frac{\partial \ln L_{it}}{\partial \ln W_{it}} = \alpha_w + \alpha_{ww} \ln W_{it} + \alpha_{yw} lnY_{it} + \alpha_{kw} \ln K_{it} \qquad (3.22)$$

Since we do not allow any interactions between the time dummies and the other regressors, the exogenous rate of technical change comprises only a neutral component (i.e., varies only over time). Therefore, following Heshmati (2001), the technical change, which is a shift the in labor demand function over time, is obtained as the elasticity of labor with respect to time.

$$E_t = \frac{\Delta \ln L_{it}}{\Delta \ln t} = \theta_t - \theta_{t-1} \qquad (3.23)$$

If $E_t > 0$, an upward shift in the labor requirement function implies that more labor-using technology is employed. If $E_t < 0$ a downward shift in the labor requirement function implies labor-saving technical progress.

Finally, the marginal variance (risk) effects E_y, ME_k, and ME_w based on $g(.)$ are calculated using the formula in equation (10). $ME_j > 0$ suggests that the variable j is variance increasing and vice versa. $ME_y > 0$ suggests that an expansion in output level increases the labor-use variance and vice versa.

Since the translog form is a point approximation of $f(.)$ with the unknown functional form, the data is normalized by the sample mean before estimating the model.

6.   Results

The empirical model and estimation procedure above are employed to estimate the labor demand function for 24 provinces of China in nine years, from 2011 to 2019. The parameter estimates of the demand function - $f(X_{it}, \alpha)$ and variance function from equation (13) - $g(X_{it}, \beta)$, are reported in Appendix A: Table A1.

6.1   Labor Demand Elasticity

The elasticities of labor demand with respect to output, wage, and capital were computed for each province each year. The labor demand elasticities with respect to all dispersion factors are both province- and time-specific. The mean values by province and year are reported in Table 2. The mean values of elasticities have consistent signs with theory: the elasticity of labor with respect to wage is negative, and the elasticities of labor with respect to output and capital are positive. The responsiveness of labor is highest to wage, followed by output and capital.

The sample mean of labor-to-wage elasticity is -0.823, with a standard deviation of 0.489. The estimate of -0.823 means that a 1 per cent increase in the wage is associated with a 0.823% decrease in labor used. A reverse U-shaped pattern is in the size of wage elasticity over time (decreasing in absolute value from 2011 to 2014 and increasing thereon until 2019); this indicates that labor adjustment with respect to wage changes due to labor market conditions slowed down until 2014 and sped up thereon. Among the 24 provinces, labor demands in Beijing, Guangdong, and Shanghai were elastic to wages, indicating that a 1 per cent increase in average wage is associated with a more than 1 per cent decrease in labor use in these provinces.

The sample mean of labor-to-output elasticity is 0.5, with a standard deviation of 0.286, meaning that a 1 per cent increase in the volume of GDP is linked with a 0.5 per cent increase in labor demand. This implies increasing returns to scale in China provinces' economies, i.e., increasing output by k% is associated with less than k% increase in labor requirement. This figure is five times the estimate for the end of the 1990s when China's employment elasticity to output was approximately 0.10 (Zhang and Cai, 2002). Although the elasticity measure was greater in 2019 (at 0.323) and on average (at 0.5), the concern relating to 'jobless growth' remains

where an economy experiences growth, e.g., increasing GDP, while its level of employment is constant or decreasing (Thomas, 2013). However, this increasing return to scale reflects improvements in China's labor performance, which may be attributed to the province-owned enterprises' reform (Zhang and Cai, 2002). Moreover, the responsiveness of labor to output considerably varies across provinces. Henan has the largest output elasticity (0.798). We conjecture that this is because Henan province has one of the highest populations in China. Two exceptions here are again found in Beijing and Shanghai, where the labor-to-output elasticity is negative.

The sample mean of labor to capital elasticity is 0.056, with a standard deviation of 0.455. Although the positive mean labor-to-capital elasticity implies that capital and labor are complements, many provinces have a negative labor-to-capital elasticity, indicating a substitution between capital and labor. The capital elasticity is highest in Shanghai (1.33), closely followed by Beijing (1.247); thus, Shanghai and Beijing are the most effective in using capital to create new jobs.

Table 2. Output, Capital and Wage Elasticities and Marginal Effects

Province/ Year	Labor demand elasticity (Ej)				Marginal variance effect (MEj)				Efficiency (9)
	GDP (1)	Capital (2)	Wage (3)	Time (4)	GDP (5)	Capital (6)	Wage (7)	Time (8)	
Mean by Province									
Anhui	0.634	-0.175	-0.543	0.003	0.052	-0.057	0.143	0.013	0.841
Beijing	-0.247	1.247	-2.059	0.003	-0.073	0.026	0.065	0	0.854
Fujian	0.538	-0.007	-0.785	0.003	-1.432	0.005	-0.429	0.008	0.865
Gansu	0.501	0.103	-0.844	0.003	0.004	0.005	-0.381	0.002	0.877
Guangdon	0.374	0.239	-1.165	0.003	-0.281	-0.615	-2.063	0.067	0.805
Guangxi	0.65	-0.175	-0.548	0.003	0.055	0.054	2.435	0.005	0.869
Guizhou	0.503	0.065	-0.752	0.003	0.025	0.028	-0.015	0.004	0.876
Hebei	0.739	-0.341	-0.391	0.003	0.292	0.09	-0.513	0.014	0.843
Heilongj	0.602	-0.067	-0.738	0.003	0.021	0.008	0.083	0.004	0.863
Henan	0.798	-0.431	-0.373	0.003	-0.179	-0.195	0.292	0.011	0.852
Hubei	0.634	-0.17	-0.608	0.003	0.065	0.285	0.062	0.034	0.821
Hunan	0.661	-0.207	-0.574	0.003	0.049	0.018	-4.793	0.007	0.869
InnerMon	0.535	0.004	-0.69	0.003	0.028	0.007	0.014	0.004	0.871
Jiangsu	0.53	-0.042	-0.741	0.003	-0.165	0.06	4.126	0.031	0.836
Jiangxi	0.658	-0.188	-0.553	0.003	0.107	-0.082	-0.113	0.007	0.856
Jilin	0.625	-0.125	-0.57	0.003	0.027	0.007	-0.026	0.006	0.848

Province/ Year	Labor demand elasticity (Ej)				Marginal variance effect (MEj)				Efficiency (9)
	GDP (1)	Capital (2)	Wage (3)	Time (4)	GDP (5)	Capital (6)	Wage (7)	Time (8)	
Liaoning	0.503	0.079	-0.94	0.003	0.111	-0.145	0.092	0.009	0.834
Shaanxi	0.616	-0.134	-0.572	0.003	0.125	0.01	0.057	0.005	0.87
Shandong	0.698	-0.302	-0.459	0.003	-0.246	0.154	-3.136	0.038	0.826
Shanghai	-0.29	1.33	-2.222	0.003	0.038	0.008	0.022	0	0.952
Shanxi	0.478	0.131	-0.958	0.003	0.016	0.008	0.527	0.003	0.868
Tianjin	0.278	0.394	-0.979	0.003	0.002	0.006	0.004	0	1
Yunnan	0.56	-0.024	-0.735	0.003	0.08	-0.065	-0.076	0.006	0.867
Zhejiang	0.426	0.149	-0.946	0.003	-0.301	-0.092	1.778	0.029	0.811
Mean by Year									
2011	0.612	-0.068	-0.857	0.000	-0.014	-0.123	-0.271	0.006	0.869
2012	0.596	-0.061	-0.803	0.005	0.034	-0.134	-0.386	0.006	0.868
2013	0.588	-0.066	-0.746	-0.019	0.236	0.020	-0.673	0.008	0.866
2014	0.572	-0.054	-0.718	0.022	0.027	0.024	0.535	0.008	0.867
2015	0.536	-0.009	-0.721	-0.034	-0.429	0.007	0.324	0.012	0.863
2016	0.494	0.050	-0.761	0.007	-0.104	-0.013	-1.360	0.013	0.862
2017	0.420	0.163	-0.872	0.145	-0.143	0.047	-0.693	0.013	0.854
2018	0.361	0.249	-0.944	-0.111	-0.110	0.004	0.900	0.024	0.853
2019	0.323	0.303	-0.983	0.012	-0.089	-0.008	0.932	0.026	0.852
Sample Mean	0.5	0.056	-0.823	0.003	-0.066	-0.02	-0.077	0.013	0.861
Standard Deviation	0.286	0.455	0.489	0.063	1.02	0.401	5.404	0.019	0.041

6.2 Technical Change

The values of the exogenous rate of technical change, defined as the shift in the labor demand function over time, are reported in Column 4 of Table 2. The sample mean value is very small and positive (0.003), indicating the technical inefficiency across time - that is, on average, the same amount of output is produced with a larger amount of labor this year than the previous year. Technical inefficiency may contribute to the slowdown of China's economic growth in recent years (The World Bank, n.d.).

6.3 Labor-Use Variance

The labor variance elasticities or marginal variance (risk) effects with respect to the output, capital, wage, and time in equation (10) were computed for each province in each year. Columns 5-8 of Table 2 report the mean values

by province and year and the overall sample mean of the marginal effect. The sample means of marginal effects of labor with respect to output, capital, and wages are negative, meaning that for provinces with production levels closer to the sample mean, the employment variance decreases when output, capital, and wages increase. Moreover, the positive relationship between labor-use variance and time indicates growing uncertainty in labor demand over the period studied.

The marginal effects across the provinces do not show any systematic patterns. We also do not observe any systematic patterns in the size of marginal effects with respect to output, capital, and wage over time.

6.4   *Labor-Use Efficiency*

Column nine of Table 2 reports the mean values by province and year of estimates of labor-use efficiency. Labor efficiency ranged between 80.5 per cent to 100 per cent with a mean of 86.1 per cent; this means that for a given level of output, on average, the labor is overused by about 14 per cent. Our finding of the mean labor-use efficiency in China is close to Kumbhakar and Zhang (2013), who found that the mean labor-use efficiency in China's manufacturing sector from 1990 to 2008 was 85.5 per cent. Table 3 reports the province- and time-specific estimates of labor efficiency.

In this paper, the labor-use efficiency is measured relative to the province with the best labor-use practice each year in our sample, which is assumed to be 100 per cent efficient. Therefore, it is noteworthy that this level of efficiency does not reflect the level of efficiency of China compared to the rest of the world. We cannot obtain absolute efficiency since the intercept, α_0, also contains the omitted province- and time effects. Therefore, with the assumption that our sample contains the most efficient province, Tianjin is found to be the province with the best labor-use practice for all years. Shanghai is the second most efficient province, with a mean efficiency of 95.2 per cent. All the remaining provinces were efficient, below 90 per cent, and the least efficient province was Guangdong, with a mean efficiency of about 80.5 per cent. This raises the question of why, despite having a high GDP, Guangdong has the least labor-use efficiency. This finding is not shocking since Liu (2019) also found that despite having the 5th highest GDP in the country, Henan was still one of the least efficient provinces. While Liu (2019) attributed this to the high population of Henan, we present the following possibilities in our context. The first reason can

be the capital-to-labor ratio of the province, i.e., Tianjin and Shanghai have capital (in billions of RMB) to labor (in thousands) ratios of 1.39 and 1.19, respectively. However, Guangdong has a very low capital-to-labor ratio of 0.27, implying that the capital stock in Guangdong is not sufficiently high enough to support efficient labor use. The second reason is the quality of human resources, which is expected to correlate positively with labor-use efficiency (Kumbhakar and Zhang, 2013). Considering the demographics, Guangdong and Beijing have large immigrant populations. However, they are very different in terms of their immigrant structure. Particularly, in Guangdong, because of the clustering of factories, most migrant laborers have relatively low education and are engaged in low-skilled employment. The opposite is true for those who migrate to Beijing, almost all of whom are highly educated and engaged in high-skilled labor. As such, the low quality of human resources in Guangdong may have led to lower labor-use efficiency. Appendix B reports the summary statistics of key variables at a provincial level.

The mean labor-use efficiency over time is declining, although at a very low rate, with an aggregate decrease of 1.7 per cent observed during the nine years (from 86.9 per cent in 2011 to 85.2 per cent in 2019). This pattern is consistent with the findings of Kumbhakar and Zhang (2013) and Cheng et al. (2020). Following Cheng et al. (2020), the decrease in labor-use efficiency over time may be due to the decreasing GDP growth rate, which consistently dropped from 9.6 per cent in 2011 to 6 per cent in 2019. Table 3 reports the labor-use efficiency across countries over time.

Table 3. Labor-Use Efficiency Across Countries and Over Time

Year Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean by Province	Std. Dev
Beijing	0.863	0.861	0.86	0.86	0.855	0.854	0.846	0.844	0.844	0.854	0.008
Tianjin	1	1	1	1	1	1	1	1	1	1	0.000
Hebei	0.850	0.849	0.849	0.85	0.845	0.844	0.835	0.834	0.834	0.843	0.007
Shanxi	0.880	0.878	0.875	0.874	0.868	0.865	0.859	0.858	0.857	0.868	0.009
InnerMon	0.881	0.88	0.877	0.877	0.872	0.87	0.862	0.862	0.862	0.871	0.008
Liaoning	0.842	0.842	0.841	0.843	0.837	0.833	0.825	0.823	0.823	0.834	0.009
Jilin	0.857	0.855	0.854	0.855	0.85	0.848	0.84	0.838	0.838	0.848	0.008
Heilongj	0.872	0.87	0.868	0.869	0.864	0.862	0.854	0.852	0.853	0.863	0.008
Shanghai	0.948	0.943	0.949	0.954	0.953	0.957	0.952	0.955	0.956	0.952	0.004

Year Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean by Province	Std. Dev
Jiangsu	0.844	0.843	0.841	0.843	0.838	0.837	0.829	0.827	0.825	0.836	0.007
Zhejiang	0.82	0.819	0.817	0.818	0.814	0.812	0.802	0.799	0.796	0.811	0.009
Anhui	0.847	0.846	0.845	0.847	0.842	0.842	0.833	0.831	0.832	0.841	0.007
Fujian	0.875	0.873	0.871	0.872	0.866	0.864	0.856	0.855	0.855	0.865	0.008
Jiangxi	0.865	0.863	0.861	0.862	0.857	0.855	0.847	0.846	0.846	0.856	0.008
Shandong	0.831	0.831	0.83	0.833	0.829	0.828	0.82	0.819	0.815	0.826	0.006
Henan	0.860	0.859	0.857	0.858	0.854	0.852	0.844	0.843	0.843	0.852	0.007
Hubei	0.827	0.827	0.827	0.828	0.824	0.823	0.814	0.811	0.813	0.821	0.007
Hunan	0.879	0.877	0.874	0.874	0.869	0.868	0.859	0.858	0.857	0.869	0.008
Guangdon	0.813	0.812	0.813	0.814	0.808	0.806	0.797	0.793	0.79	0.805	0.009
Guangxi	0.878	0.876	0.874	0.874	0.87	0.869	0.861	0.86	0.859	0.869	0.007
Guizhou	0.884	0.882	0.881	0.882	0.878	0.877	0.869	0.867	0.867	0.876	0.007
Yunnan	0.875	0.873	0.871	0.871	0.867	0.866	0.859	0.858	0.86	0.867	0.006
Shaanxi	0.881	0.879	0.876	0.876	0.871	0.869	0.86	0.859	0.86	0.87	0.009
Gansu	0.885	0.884	0.882	0.882	0.878	0.876	0.87	0.87	0.868	0.877	0.007
Mean by Year	0.869	0.868	0.866	0.867	0.863	0.862	0.854	0.853	0.852	0.861	
Std. Dev	0.039	0.039	0.04	0.04	0.041	0.041	0.043	0.044	0.045		0.041

Table 4 shows the frequency distribution of labor-use efficiency. The labor-use efficiency levels of most provinces across different years fall between 81.1 per cent to 88 per cent.

Table 4. Labor-Use Efficiency Frequency Distribution.

Percentage efficiency interval	Frequency	Percentage
00.0 – 81.0	8	3.7
81.1 – 86.0	111	51.39
86.1 – 88.0	69	31.94
88.1 – 90.0	10	4.63
94.1 – 96.0	9	4.17
98.1 – 100.0	9	4.17

7.   Conclusion

This paper investigates the labor-use efficiency of 24 provincial-level administrative regions/provinces across China from 2011 to 2019. The labor-

use efficiency is estimated as the mean of a stochastic labor requirement frontier function. A flexible translog function is used to represent the labor demand, defined as a function of output (GDP), average wages, capital stock, province-specific variables that characterize the nature of the technology and production environment, and time variables. The variance function appears multiplicatively with the demand function, accommodating both positive and negative marginal effects. A multi-step procedure is used to estimate the parameters of the demand and variance models using generalized least squares and a weighted nonlinear method, respectively.

We observe an increasing return to scale in output, indicating that increasing output by k% would increase labor requirement by less than k%. The wage elasticity has a U-shape pattern in magnitude across time, with the highest elasticity of -0.983 in 2019, indicating that adjustments in labor force participation across China have become more responsive in recent years. Moreover, although minute, the positive labor-to-capital elasticity indicates that labor and capital are complements. On the other hand, a very small but positive exogenous rate of technical change (0.003) indicates that, on average, provinces are becoming less efficient in labor use over time. Moreover, the negative marginal variance effects with respect to output, capital, and wages indicate that the variance in labor used decreases with increases in these three factors.

Relating to labor-use efficiency, we observe that, on average, there is a potential for reducing labor demand by up to 13.9 per cent. While Tianjin, followed by Shanghai, is the most efficient province (100 per cent and 95.2 per cent, respectively), all the remaining provinces are less than 88 per cent efficient, indicating that there is potential for improved efficiency by at least more than 12 per cent. At the same time, Guangdong is the least efficient province and could improve its labor efficiency by about 19.5 per cent. Furthermore, the declining mean labor-use efficiency over time indicates that other provinces (relative to the most efficient province) are slower in improving their efficiency over time.

The findings of this paper demonstrate that policies across Chinese provinces should be targeted at further enhancing labor-use efficiency to encourage sustained economic growth. A key policy implication of our findings is to improve labor-use efficiency across the less efficient provinces. This can be achieved by narrowing the gap between Tianjin and labor-use efficiency, which should be a focus of policies in China.

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Appendix A: Parameter Estimates

Table A1. Parameter Estimates of Labor Demand Function and Variance Function

Parameter	Estimate		SE	Parameter	Estimate		SE	Parameter	Estimate		SE
Labor demand function											
α_0	-0.77	***	0.2578	θ_6	-0.01497		0.0306	μ_{14}	0.228695		0.3359
α_y	0.504678	**	0.2475	θ_7	0.09479	***	0.0235	μ_{15}	0.747856	*	0.4207
α_w	-0.6021	*	0.3499	θ_8	0.007687		0.0358	μ_{16}	0.288372		0.4126
α_k	-0.02305		0.088	θ_9	0.038461		0.0415	μ_{17}	0.732089	**	0.3497
α_{yy}	-0.08062		0.2081	μ_2	-0.57181	**	0.2621	μ_{18}	-0.02791		0.3556
α_{ww}	-0.38232		0.2819	μ_3	0.424711		0.3498	μ_{19}	0.57615		0.5362
α_{kk}	-0.22722	*	0.1237	μ_4	0.091251		0.314	μ_{20}	0.02878		0.3316
α_{yw}	-0.44529		0.3761	μ_5	0.006623		0.301	μ_{21}	-0.00649		0.3008
α_{yk}	0.144472		0.197	μ_6	0.451254		0.3189	μ_{22}	0.009661		0.3322
α_{wk}	0.992133	***	0.2426	μ_7	0.414705		0.3239	μ_{23}	0.027532		0.3172
η_1	0.483309	**	0.2042	μ_8	0.128668		0.3488	μ_{24}	0.077729		0.3275
η_2	-0.1541	***	0.0469	μ_9	-0.58273	***	0.1612				
θ_2	0.004585		0.0358	μ_{10}	0.39543		0.4636				
θ_3	-0.02237		0.0362	μ_{11}	0.676376	**	0.3417				
θ_4	0.016236		0.0354	μ_{12}	0.435654		0.3251				
θ_5	-0.04201		0.0334	μ_{13}	0.199804		0.3233				
$R^2 = 0.9878$											
Variance function											
β_y	0.001962		0.0213								
β_k	-0.01851		0.0208								
β_w	0.166665	***	0.0269								
β_t	-0.00997	**	0.00413								
$\sigma_v^2 = 5.7773$											

*Note: *p<0.1, ** p<0.05, *** p<0.01. The dependent variable is the amount of labor used per province. The number of observations is 243.*

Appendix B: Summary Statistics by Province

Table A2. Summary Statistics by Province

Anhui

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	5293.8	1770.5	3278.0	8298.0
GDP (billion RMB)	2537.8	699.2	1628.5	3684.6
Capital (billion RMB)	2417.2	783.6	1245.6	3574.1
Average Wage (thousand RMB)	57.3	13.5	39.4	79.0
Research and Development (number of projects)	1573.9	493.0	842.6	2579.9
Province Government Expenditure (billion RMB)	524.5	131.9	330.3	739.2

Beijing

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	965.0	145.2	716.0	1124.0
GDP (billion RMB)	2561.4	627.9	1718.9	3544.5
Capital (billion RMB)	721.1	92.1	557.9	837.0
Average Wage (thousand RMB)	114.6	29.7	75.5	166.8
Research and Development (number of projects)	797.2	99.4	703.9	1003.7
Province Government Expenditure (billion RMB)	549.7	163.0	324.5	747.1

Fujian

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	4244.9	2424.5	2212.0	9688.0
GDP (billion RMB)	2853.8	834.6	1791.8	4232.7
Capital (billion RMB)	2082.9	746.6	991.1	3119.2
Average Wage (thousand RMB)	58.7	14.2	38.6	81.8
Research and Development (number of projects)	1300.3	487.8	644.1	2168.9
Province Government Expenditure (billion RMB)	378.4	103.1	219.8	507.8

Gansu

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	1882.7	566.3	1149.0	2953.0
GDP (billion RMB)	670.7	123.8	481.7	871.8
Capital (billion RMB)	659.3	182.8	396.6	966.4
Average Wage (thousand RMB)	53.1	14.5	32.1	73.6
Research and Development (number of projects)	161.3	23.0	128.0	191.2
Province Government Expenditure (billion RMB)	287.1	75.0	179.1	395.2

Guangdong

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	11263.4	3338.7	6938.0	15669.0
GDP (billion RMB)	7747.0	1933.7	5307.3	10798.7
Capital (billion RMB)	3045.3	1028.2	1706.9	4644.2
Average Wage (thousand RMB)	68.1	18.2	45.1	98.9
Research and Development (number of projects)	5503.1	2526.7	2924.3	10634.0
Province Government Expenditure (billion RMB)	1177.8	393.3	671.2	1729.8

Guangxi

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	3278.6	977.2	2172.0	5031.0
GDP (billion RMB)	1524.6	376.0	1030.0	2123.7
Capital (billion RMB)	1623.6	584.0	799.1	2489.3
Average Wage (thousand RMB)	53.1	15.3	33.0	76.5
Research and Development (number of projects)	302.7	47.1	239.7	393.7
Province Government Expenditure (billion RMB)	408.8	112.6	254.5	585.1

Guizhou

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	2577.4	986.0	1202.0	4214.0
GDP (billion RMB)	1084.1	386.1	561.6	1676.9
Capital (billion RMB)	1134.2	516.9	423.6	1811.5
Average Wage (thousand RMB)	59.6	16.6	36.1	83.3
Research and Development (number of projects)	218.1	81.7	134.5	385.0
Province Government Expenditure (billion RMB)	393.6	116.9	224.9	594.9

Hebei

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	6128.4	2263.9	3894.0	9822.0
GDP (billion RMB)	2743.5	454.9	2138.5	3497.9
Capital (billion RMB)	2818.3	727.6	1638.9	3771.3
Average Wage (thousand RMB)	52.4	13.5	35.3	73.0
Research and Development (number of projects)	915.6	218.3	605.5	1334.0
Province Government Expenditure (billion RMB)	567.3	165.6	353.7	830.9

Heilongjiang

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	3206.4	656.3	2498.0	4586.0
GDP (billion RMB)	1191.8	103.3	993.5	1354.4
Capital (billion RMB)	1030.8	125.1	747.5	1145.3
Average Wage (thousand RMB)	48.8	11.9	31.3	68.4
Research and Development (number of projects)	363.7	70.4	263.1	434.3
Province Government Expenditure (billion RMB)	392.7	77.1	279.4	501.2

Henan

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	6333.2	2118.1	4005.0	10207.0
GDP (billion RMB)	3858.9	941.6	2631.9	5371.8
Capital (billion RMB)	3519.0	1202.2	1776.9	5194.9
Average Wage (thousand RMB)	48.0	11.8	33.6	67.3
Research and Development (number of projects)	1361.5	468.7	841.5	2381.0
Province Government Expenditure (billion RMB)	696.8	197.3	424.9	1016.4

Hubei

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	8687.0	2207.7	4777.0	11095.0
GDP (billion RMB)	3161.5	868.4	1994.3	4542.9
Capital (billion RMB)	2608.0	924.0	1255.7	3966.8
Average Wage (thousand RMB)	55.9	15.1	36.1	79.3
Research and Development (number of projects)	1084.4	325.6	707.7	1742.4
Province Government Expenditure (billion RMB)	565.2	165.0	321.5	797.0

Hunan

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	4058.9	768.5	3235.0	5351.0
GDP (billion RMB)	2877.7	707.8	1891.5	3989.4
Capital (billion RMB)	2496.7	934.0	1188.1	3870.6
Average Wage (thousand RMB)	53.6	14.0	34.6	74.3
Research and Development (number of projects)	1042.1	482.7	664.6	2121.2
Province Government Expenditure (billion RMB)	575.5	154.5	352.1	803.4

Inner Mongolia

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	2791.4	553.5	1659.0	3244.0
GDP (billion RMB)	1316.3	259.4	945.8	1721.3
Capital (billion RMB)	1306.8	251.2	1004.7	1759.2
Average Wage (thousand RMB)	59.0	12.9	41.1	80.6
Research and Development (number of projects)	206.6	34.4	132.0	235.3
Province Government Expenditure (billion RMB)	413.4	69.0	298.9	510.1

Jiangsu

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	7851.7	2328.5	5330.0	11937.0
GDP (billion RMB)	7256.2	1754.2	4883.9	9865.7
Capital (billion RMB)	4448.1	1135.8	2669.3	5907.4
Average Wage (thousand RMB)	67.9	16.5	45.5	96.5
Research and Development (number of projects)	5825.3	1835.2	3193.3	9524.0
Province Government Expenditure (billion RMB)	933.8	212.7	622.2	1257.4

Jiangxi

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	3900.4	530.0	3161.0	4753.0
GDP (billion RMB)	1745.8	444.2	1158.5	2466.7
Capital (billion RMB)	1758.8	617.6	908.8	2679.4
Average Wage (thousand RMB)	52.4	13.7	33.2	73.7
Research and Development (number of projects)	719.7	544.3	260.8	1864.5
Province Government Expenditure (billion RMB)	434.5	125.5	253.5	638.7

Jilin

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	3557.9	1138.6	2124.0	5367.0
GDP (billion RMB)	1001.7	126.5	773.5	1172.7
Capital (billion RMB)	1144.3	215.8	744.2	1392.3
Average Wage (thousand RMB)	52.5	13.6	33.6	73.8
Research and Development (number of projects)	255.9	146.4	171.5	642.1
Province Government Expenditure (billion RMB)	317.6	62.5	220.2	393.3

Liaoning

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	4581.6	648.4	3645.0	5455.0
GDP (billion RMB)	2045.6	263.7	1635.5	2485.5
Capital (billion RMB)	1495.1	812.3	667.7	2510.8
Average Wage (thousand RMB)	53.7	11.7	38.2	72.9
Research and Development (number of projects)	787.5	151.7	542.2	1037.0
Province Government Expenditure (billion RMB)	486.3	54.8	390.6	574.5

Shaanxi

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	3359.6	1214.4	2074.0	5907.0
GDP (billion RMB)	1864.2	445.9	1217.5	2579.3
Capital (billion RMB)	1889.2	615.7	943.1	2695.4
Average Wage (thousand RMB)	56.6	13.4	38.1	78.4
Research and Development (number of projects)	515.3	94.1	405.4	666.8
Province Government Expenditure (billion RMB)	427.8	91.2	293.1	571.9

Shandong

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	10222.8	4086.3	5789.0	18493.0
GDP (billion RMB)	5493.3	1078.8	3906.5	7054.1
Capital (billion RMB)	4492.8	1115.5	2675.0	5746.6
Average Wage (thousand RMB)	57.9	14.8	37.6	81.4
Research and Development (number of projects)	3596.9	754.5	2519.3	4662.5
Province Government Expenditure (billion RMB)	798.6	193.4	500.2	1074.0

Shanghai

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	540.3	85.5	446.0	679.0
GDP (billion RMB)	2816.5	644.1	2001.0	3798.8
Capital (billion RMB)	641.5	108.2	496.2	801.2
Average Wage (thousand RMB)	110.5	26.4	75.6	149.4
Research and Development (number of projects)	1256.7	103.3	1090.9	1382.1
Province Government Expenditure (billion RMB)	608.2	174.9	391.5	835.2

Shanxi

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	2773.0	824.5	1835.0	4163.0
GDP (billion RMB)	1309.4	215.2	1089.4	1696.2
Capital (billion RMB)	966.7	330.8	604.1	1419.8
Average Wage (thousand RMB)	53.3	10.1	39.2	69.6
Research and Development (number of projects)	288.7	53.1	223.2	382.6
Province Government Expenditure (billion RMB)	342.7	73.7	236.4	471.1

Tianjin

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	744.1	291.3	436.0	1258.0
GDP (billion RMB)	1110.7	195.5	811.3	1405.6
Capital (billion RMB)	1036.2	194.0	706.8	1277.9
Average Wage (thousand RMB)	80.8	18.0	55.7	108.0
Research and Development (number of projects)	1218.5	142.4	1051.5	1505.5
Province Government Expenditure (billion RMB)	291.6	64.0	179.6	369.9

Yunnan

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	3499.3	760.8	2440.0	4811.0
GDP (billion RMB)	1571.2	450.8	952.3	2322.4
Capital (billion RMB)	1423.4	592.4	619.1	2292.9
Average Wage (thousand RMB)	56.1	18.1	34.0	86.6
Research and Development (number of projects)	312.1	158.2	151.4	628.6
Province Government Expenditure (billion RMB)	481.4	122.6	293.0	677.0

Zhejiang

Variable	Mean	Std. Dev.	Min	Max
Labor (thousand)	7187.9	1656.1	5215.0	9675.0
GDP (billion RMB)	4524.7	1063.4	3185.5	6246.2
Capital (billion RMB)	2638.5	776.6	1418.5	3734.1
Average Wage (thousand RMB)	69.2	18.1	45.2	99.7
Research and Development (number of projects)	5652.7	2221.1	2867.2	9850.1
Province Government Expenditure (billion RMB)	641.4	211.7	384.3	1005.3