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# Does gender structure influence R&D efficiency? A regional perspective

**Mingting Kou[1] · Yi Zhang[2] · Yu Zhang[3] · Kaihua Chen[3] · Jiancheng Guan[4] · Senmao Xia[5]**

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**Abstract**
The gender structure in research and development (R&D) activities has received more and more attention in terms of its increasing importance in R&D management, but it is still not clear what the R&D efficiency discrepancy between female and male personnel is in the science and technology (S&T) field and whether the gender structure affects the R&D efficiency. Based on the region-level panel dataset of China's research institutes, this study uses four types of R&D outputs (papers, books, patents and standards) together and individually to measure R&D efficiency score to reveal this topic. When four types of R&D outputs are jointly considered, this paper applies the multi-output stochastic frontier analysis and finds that in general the higher proportion of male R&D personnel produces the higher R&D efficiency. Nevertheless, in terms of S&T papers or S&T books as a single R&D output, we find that the higher proportion of female R&D personnel leads to the higher R&D efficiency. On the contrary, the R&D efficiency is lower with the higher proportion of female R&D personnel when the single R&D output is measured by invention patent applications or national/industrial standards, respectively. Our findings suggest that the female R&D personnel are more effective in conducting scientific research activities, while their counterparts are more effective in doing technology development activities.

**Keywords** R&D efficiency · Gender structure · Gender gap · China's research institutes · Region-level analysis

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✉ Yu Zhang
zhangyu_00613@163.com; 28828627@qq.com

Extended author information available on the last page of the article

## Introduction

The determining of research and development (R&D) efficiency has become a research hotspot in academia (e.g., Broekel 2012, 2015; Chen and Guan 2012; Fritsch and Slavtchev 2007, 2010, 2011; Wang and Huang 2007). The extant literature classifies the determinants influencing R&D efficiency into the external and internal ones. More specifically, the external determinants include fiscal incentive policies, intellectual property, external collaboration or network and so on, and the internal determinants cover internal collaboration or network, allocation of R&D expenditure, gender gap of R&D personnel and so on. Currently, extant literature largely focuses on the effects of external variables on R&D efficiency, while limited attention is paid to the internal variables' impacts. An interesting internal variable, namely, the gender structure measured by the proportion of female or male R&D personnel, has been neglected in the extant literature on R&D efficiency. As a result, relatively little is known about what the R&D efficiency gap between females and males is in the science and technology (S&T) field, and whether the gender structure influences the R&D efficiency or not.

In fact, the endeavor to reveal the association between gender structure and R&D efficiency is of particular importance and necessary as it can provide some significant implications for governments and policy makers, who have been trying to take some effective research policies to create a favorable institutional arrangement to achieve gender equality in the S&T field. In this context, the issue regarding what the gender difference or gap is in S&T field has attracted more and more attention of scholars in multiple aspects, such as Ceci et al. (2014) in research and academic career, Contini et al. (2017) in mathematics achievement and Jappelli et al. (2017) in research evaluation. However, extant literature is characterized by mixed findings. For example, some studies reported the higher R&D performance in favor of either the low gender difference (e.g., Hülsheger et al. 2009; Pelled et al. 1999) or the high one (e.g., Van Dijk et al. 2012), while other studies demonstrated no discernable gender difference (e.g., Lerchenmueller and Sorenson 2018; Nielsen 2016). Clearly, there is ambiguous evidence for the links between gender diversity and R&D performance, indicating more empirical studies are needed to clarify the debate regarding the effect of gender diversity on R&D performance. This topic is more interesting from the R&D-efficiency perspective, which can more effectively uncover the gender difference from a R&D process perspective since the gender structure directly affects the R&D process.

Investigating the relationships between gender diversity and R&D performance is a difficult task in both conceptual and methodological challenges. The existing literature primarily focuses on how the group performance measured by research outcomes is influenced by gender differences, ignoring the gender gap in R&D efficiency related to the input–output relationship of R&D activities (e.g., De 2013; Frietsch et al. 2009; Hunt et al. 2013; Jung and Ejermo 2014; Meng 2016). In fact, the impact of the gender structure on R&D efficiency is an important subject for policy-makers and academic researchers. This helps us to enrich the understanding of R&D performance by encompassing the input–output relationship of R&D activities.

To have a more comprehensive and rigorous understanding the effect of the gender structure on R&D efficiency, this study adopts multiple types of R&D outputs together or individually to measure the R&D efficiency score. It is well known that R&D activities can split into two subgroups: the science research activities and the technology development activities (Lo 2010). The former is focused on the discovery of truth by basic research activities, whilst the latter is about the application of truth by technology development activities (Pinch and Bijker 1984). Correspondingly, the S&T papers and books are deemed as the typical outputs of scientific research activities, while the invention and application of patents as well as national/industrial standards are considered as the important outputs of technology development activities. This study will explore the difference in the impact of gender structure on the R&D efficiency in the case of different R&D outputs. We will first explore whether the male and female R&D personnel have divergent R&D efficiency scores measured by different types of R&D outputs. If it is the case, we then clarify what exactly is the status of the gender gap in R&D efficiency and whether the gender structure affects the R&D efficiency in different S&T fields.

In contrast to the existing literature, this study makes two prominent contributions. First, this study proposes a new topic which is to explore the impact of gender structure on the R&D efficiency in different S&T fields from the input–output transformation perspective. This is in sharp contrast with extant literature which investigates the gender gap in patenting or/and publishing only from the R&D output perspective (e.g., De 2013; Frietsch et al. 2009; Hunt et al. 2013; Jung and Ejermo 2014; Meng 2016). In this sense, this study enriches the literature about the gender gap in S&T studies. Second, this paper, as an exploratory study introducing a modified method to measure the R&D efficiency with multiple types of R&D outputs, enriches the literature regarding the assessment of R&D efficiency. More specifically, different from extant studies that usually adopt Data Envelopment Analysis (DEA) method to measure R&D efficiency and further employ Tobit regression analysis to investigate the determining factors (e.g., Wang and Huang 2007; Chen and Guan 2012), this study adopts the multi-output Stochastic Frontier Analysis (SFA) to overcome the shortcoming of DEA in time series. The introduction of modified SFA model also riches the extant R&D efficiency literature based on one-output SFA model (e.g., Fritsch and Slavtchev 2010; Fu and Yang 2009).

The rest of this study is structured as follows. Relevant concepts, research frames and gender gap theories have been introduced in the second section. The third section deals with the data source and economic model. The fourth section focuses on the empirical analysis. The conclusions and discussions are presented in the last section.

## Theoretical basis

With increasing resources devoted to S&T in the knowledge-driven economy (Romer 1986), how to improve R&D efficiency has become an important issue for policy-makers and academic researchers. In this situation, the R&D efficiency has been deemed as a critical index for evaluating the operational performance of R&D activities (Fritsch and Slavtchev 2010). The R&D efficiency score is used to reflect the transformation process performance from R&D inputs to R&D outputs (Cefis and Marsili 2011) which is also called as a knowledge creation process. In fact, the knowledge creation process originates from the standard knowledge production function, which was proposed by Griliches (1979) to quantitatively formulate the knowledge production process. Existing studies consider the R&D process as the knowledge production process and measure this process by one specific production function, namely, the standard production function. This function is usually introduced as the basic analysis model, and the specialized influence factors are added into this function to examine their effects on the R&D process (e.g., Fritsch and Slavtchev 2007, 2010; Cefis and Marsili 2011).

The standard production function is based on one hypothesis that all production units own the same production technology and the resource is allocated optimally. In this case, equal outputs will be gained if the inputs are equal and the inefficiency is not considered. However, Kumbhakar and Lovell (2003) found that the same inputs don't necessarily produce the same amount of outputs even if all units own the same production technology. The reason is that the production process is jointly affected by both external and internal: the former one includes such as regime circumstance, finance circumstance, policy circumstance, whilst the latter one includes such as gender structure, allocation structure and collaboration network. Similar to the general production function, the R&D process presented by a knowledge production function is also one type of production process and, therefore, is jointly affected by both internal and external factors.

The gender structure of R&D personnel is an internal factor and its influence on R&D efficiency can be explained by different theoretical approaches, among which the cognitive resource diversity and the similarity-attraction paradigm theory are the most important ones (De Saá-Pérez et al. 2017; Horwitz 2005). Specifically, the cognitive resource diversity theory states that a group composed of diversified members likely has a better performance because of the unique combination of different cognitive perspective and resources that diversified members bring to the group (Hambrick et al. 1996). In other words, the diversity would have an additional effect on a group's performance. When the diversity between members is discussed in terms of the level of gender structure in a group, it is closely linked with cognitive traits of females and males. Many studies find that there is a big difference between male and female in the brain structure (Allen et al. 2003; Chen et al. 2007; Ruigrok et al. 2014) as well as brain function (Andreason et al. 1994; Bell et al. 2006; George et al. 1996; Kawachi et al. 2002). This difference in brain usually results in a gender gap in cognition ability (Yang et al. 2015), which influences the forming of perceptual views and solutions for problems (Dutton and Duncan 1987). Therefore, the gender diversity would provide a research group with a larger pool of cognitive perspectives and resources that may be helpful in dealing with S&T problems, helping to explain why the diversity has a positive effect on the group's performance.

Otherwise, the similarity-attraction paradigm theory stresses that the similarity of characteristics among group members contributes to promoting mutual attraction among members (Byrne et al. 1986; Horwitz 2005), which could strengthen the social integration and cohesion among group members (O'Reilly et al. 1989). In this sense, a group composed of diversified members would likely demonstrate an unfavorable signs of high relationship conflict and internal tensions. This would have an adverse effect on the group's performance. By contrast, in homogeneous group, the similarity of individuals' characteristics could promote mutual interactions, which would help to promoting the R&D process and efficiency (Horwitz 2005; Van Knippenberg and Schippers 2007).

Overall, these two theoretical perspectives offer complementary views on the conditions shaping the link between gender structure and R&D efficiency. On the one hand, the cognitive resource diversity theory stresses that the diversity has an additional effect on the creative and innovative outcomes in a group; on the other hand, the similarity-attraction paradigm theory states that the diversity lowers the level of group cohesion (Lungeanu and Contractor 2015). These mixed arguments are supported by previous studies which presented ambiguous evidence for the effect of gender diversity on group performance (Almor et al. 2019; Chatman and O'Reilly 2004; Joshi and Roh 2009; Myaskovsky et al. 2005). It should be noted that most theoretical and empirical studies are limited to concerning single dimension of R&D outputs in isolation, such as publication and citation impact (Nielsen and Börjeson 2019), patents or revenues of new products (Cheung and Ping 2004; De

2013; Hunt et al. 2013; Jung and Ejermo 2014; Siegel et al. 2003a, b). Few studies have comprehensively distinguished the different effects of gender diversity on different research outputs including invention patents, S&T papers, S&T books and standards, especially from the efficiency perspective.

As mentioned earlier, there is a big difference between male and female in their cognition abilities and perceptual views (Dutton and Duncan 1987; Yang et al. 2015), indicating the man and woman may have different advantages and disadvantages in implementing different S&T activities. This can also be interpreted from either the biological perspective, such as gene and brain, or the social perspective, including social burden and social bias. From the social perspective, the main obligation of females is traditionally considered as taking care of their family (Frietsch et al. 2009), which usually leads females to devote less time or efforts on work (Greenhaus and Beutell 1985; Jacobs and Gerson 2004; Nomaguchi 2009; Zhang et al. 2008). Nevertheless, with the development of society, last decades witnessed a significant increase in females' involvement in higher education as well as R&D activities (Leemann 2010). Many studies, however, find that there still exists a significant gender gap in moving up in the academic career ladder. For instance, females are more likely to face barriers in their career than males (McWhirter 1997), and less access to academic resources and social capital (Leemann 2010). In addition, female researchers have less geographically mobility than their male counterparts in general (Mcbrier 2003).

From a biological perspective, the gender difference in personality traits between males and females has been documented consistently for Neuroticism, Agreeableness, Extraversion, Conscientiousness, Openness and Intellect (Baron-Cohen et al. 2001; Goodwin and Gotlib 2004), which may affect the R&D output discrepancy between female and male personnel. Some studies concluded that the male has better spatial cognition ability while the female's lingual ability, such as speaking and writing, is better (Claster and Blair 2013). Furthermore, there is gender difference in the ability of calculation, induction as well as STEM (Science, Technology, Engineering and Mathematics). For example, Contini et al. (2017) found that there is an obvious gender gap in mathematics score and girls usually have less self-confidence and more stress in the activities related to mathematics (Lubienski et al. 2013; Twenge and Campbell 2001). This phenomenon exists in almost every family structure, ethnic group, and level of the socio-economic distribution (Fryer and Levitt 2010).

Due to significant gender difference, the male and female personnel might have different advantages of producing different types of R&D outputs, such as invention patents, S&T papers, S&T books and national/industrial standards. However, this assumption has not been verified in the extant research. To fill this research gap, this study will explore whether the gender structure of R&D personnel has influenced the R&D efficiency (i.e., the level of R&D outputs in the given R&D inputs) or not.

## Method

### Estimation method

R&D efficiency reflects the transformation effectiveness from R&D inputs to outputs, and our study will analyze whether this process is affected by the gender structure of R&D personnel or not. For the research purpose, the general modeling approach for measuring efficiency and examining influence factors is a two-step DEA-regression method (i.e., Chen and Guan 2012; Liu et al. 2017; Watcharasriroj and Tang 2004). DEA is a nonparametric method for which a specific kind of production function form is unnecessary. Compared with the traditional one-output SFA, DEA is still effective when measuring multiple R&D outputs. However, DEA is not effective for time series data. This is not the case for SFA, which uses maximum likelihood estimation (MLE) to estimate the parameters and then uses conditional expectation to calculate the technical efficiency of each decision unit. This method makes full use of the information of each sample and treats each sample equally. Therefore, the efficiency calculation results of SFA are relatively stable and are not affected by abnormal points. However, the measurement results of R&D efficiency scores based on DEA are much susceptible (Tavana et al. 2014) and are vulnerable to the influence of abnormal points when data lies in the frontier. Because DEA constructs the frontier from technically effective samples, the performance of these samples ultimately determines the shape of frontier, and then largely determines R&D efficiency calculation results of all production units. If there are abnormal points in samples, the measurement results based on DEA would be greatly affected and the errors would occur. To overcome these limitations, this study adopts SFA (e.g., Broekel 2012, 2015; Fritsch and Slavtchev 2007, 2010, 2011) rather than DEA-regression to investigate our research topic.

Based on MLE, the SFA can overcome the adverse impact of statistical noise and random environmental factors on efficiency measures (Li 2009). SFA is convenient in capturing the effect of factors meanwhile calculating efficiency scores. According to Aigner et al. (1977) and Meeusen and Van Broeck (1977), the SFA model incorporating the influence factors on efficiency scores is as follows:

$$y_{lt} = f\left(x_{lt}, t\right) \cdot \exp\left(v_{lt} - u_{lt}\right), \quad (l = 1, 2, \ldots, L; t = 1, 2, \ldots, T), \tag{1}$$

where $y_{lt}$ denotes the real output of production unit $l$ in period $t$; $x_{lt}$ is the input vector; it will be $x_{lt} = \left(x_{lt1}, x_{lt2}, \ldots, x_{ltk}\right)$ if we have $k$ kinds of input elements; $f\left(x_{lt}, t\right)$ is the production possibility frontier; $v_{lt}$ is a random variable independent of the $u_{lt}$, i.e., $v_{lt} \sim N(0, \sigma_v^2)$; $u_{lt}$ is a non-negative random variable, which is assumed to account for technical inefficiency.

Considering that technical efficiency of firms may vary over time, we follow Battese and Coelli (1992) and specify $u_{lt}$ as follows:

$$u_{lt} = (U_l \exp(-\eta(t - T))), \quad (l = 1, 2, \ldots, L; t = 1, 2, \ldots, T), \tag{2}$$

where $u_{lt}$ is assumed to be non-negative truncations of the $N^{+}(u, \sigma_u^2)$ distribution; $\eta$ is an unknown scalar parameter. If $\eta = 0$, $\eta < 0$ or $\eta > 0$ denote that $u_{lt}$ remains constant, increases, or decreases as $t$ increases, respectively.

In our model, $f(x_{lt}, t) \cdot \exp\left(v_{lt}\right)$ presents the production possibility frontier, and the R&D efficiency $\mathrm{EFF}_{lt}$ is defined as the ratio of real output to expectation of random frontier output. The equation is expressed as follows:

$$\mathrm{EFF}_{lt} = \frac{E(f(x_{lt}, t)\exp(v_{lt} - u_{lt}))}{E(f(x_{lt}, t)\exp(v_{lt})|u_{lt} = 0)} \quad \text{(Single-type output)} \tag{3}$$

$$\mathrm{EFF}_{lt} = \frac{E(f(x_{lt}, \theta_{lt}(y), w) \cdot \exp(v_{lt} - u_{lt}))}{E(f(x_{lt}, \theta_{lt}(y), w) \cdot \exp(v_{lt})|u_{lt} = 0)} \quad \text{(Multiple-type outputs)} \tag{4}$$

Obviously, if $u_{lt}$=0, then $\mathrm{EFF}_{lt}$=1, which means the production unit is efficient and all eclipse of points is caused by random variable $v_{lt}$. If $u_{lt} > 0$, then $\mathrm{EFF}_{lt} < 1$, which denotes that there exists non-efficiency. In terms of multiple-type outputs (including S&T papers, S&T books, invention patent applications and national/industrial standards). The traditional one-output SFA model can overcome the drawbacks of DEA, but it is not applicable for measuring efficiency in the case of multiple outputs (Henningsen et al. 2015; Löthgren 1997). To overcome this weakness, this study follows Löthgren's (1997) proposition and adopts a multi-output SFA model, which adds the concept of Shephard Distance Function into the SFA model.

According to the output-oriented distance function, in the case of single-type output, there are the following distance functions:

$$D_o(x, y, w) = \inf\left\{\delta \in R_{++} : \frac{y}{\delta} \in Z(x, w),\quad w \in \Omega\right\}, \tag{5}$$

where $y$ is output, $Z(x, w)$ is possibility-space output, and $Z(x, w) = \{y \in R_+ : y = f(x, w), w \in \Omega\}$; $f(x, w)$ represents the production function of $x$ under state $t$, and $\Omega$ is the set of various production states. The value of the output distance function is obtained by comparing the actual output vector norm with the vector norm on the random frontier in the same direction as the actual output vector. Based on this principle, the distance function in the case of $p$ kinds of outputs $y = \left(y_1, y_2, \dots, y_P\right)$ is defined as follows:

$$D_o(x, y, w) = \frac{||l(y) \cdot m(\theta(y))||}{||f(x, \theta(y), w) \cdot m(\theta(y))||} = \frac{l(y)}{f(x, \theta(y), w)}, \tag{6}$$

where $y = \left(y_1, y_2, \dots, y_p\right) = l(y) \cdot m(\theta(y))$, $l(y)$ is the second order norm of $y$ and $l(y) = ||y||$, $m(\theta(y))$ is the angle cosine vector of the output vector, and $m(\theta(y)) = (m_1(\theta), m_2(\theta), \dots, m_P(\theta))$, $m(\theta) = y/l(y)$, $m_i(\theta) = \cos\theta_i \cdot \Pi_{j=0}^{i-1} \sin\theta_j$ $(i = 1, 2, 3, \dots, p), \theta = \theta(y) = \left(\theta_1(y), \theta_2(y), \dots, \theta_{P-1}(y)\right) \in \left[0, \pi/2\right]^{p-1}, \sin\theta_0 = \cos\theta_P = 1,$ and $||m(\theta)|| = 1$. The formula for calculating $\theta_i(y)$ is as follows:

$$\theta_i(y) = \text{arc}\cos(m_i(\theta)/\Pi_{j=0}^{i-1}\sin\theta_j), \quad (i = 1, 2, 3, \dots, p). \tag{7}$$

Moreover, $f(x, \theta(y), w)$ is the deterministic core of the stochastic frontier of multiple outputs, and $f(x, \theta(y), w) = \max\{d \in R_{++} : d \cdot m(\theta(y)) \in Z(x, w),\ w \in \Omega\}$. Therefore, $f(x, \theta(y), w) \cdot m(\theta(y))$ is on the frontier, and this frontier is $IsopZ(x, w) = \{y : y \in Z(x, w), \lambda y \notin Z(x, w), \lambda > 1\}$. Based on the above analysis, there is the following frontier function model including distance function:

$$l(y) = f(x, \theta(y), w) \cdot D_o(x, y, w). \tag{8}$$

According to Meeusen and Broeck (1977), two random variables $v$ and $u$ are introduced into the model. The random frontier output norm is expressed by $f(x, \theta(y), w) \cdot \exp(v)$, and the random output distance function $D_o(x, y, w)$ is expressed by $\exp(-u)$, where $u$ is also a non-negative term. By taking logarithms on both sides of the above formula, the following generalized stochastic frontier model with multiple outputs is obtained:

$$\begin{cases} \ln l(y) = \ln f(x, \theta(y), w) + v - u, \quad \theta(y) = (\theta_1(y), \theta_2(y), \dots, \theta_{p-1}(y)) \in [0, \pi/2]^{p-1} \\ \theta_i(y) = \text{arc}\cos(m_i(\theta)/\Pi_{j=0}^{i-1}\sin\theta_j), \ (i = 1, 2, 3, \dots, p-1) \end{cases} \tag{9}$$

For $T$-period panel data with $L$ production units, there are $k$ kinds of inputs and $p$ kinds of outputs for each production unit, the corresponding panel data model is as follows:

$$\begin{cases} \ln l(y_{lt}) = \ln f(x_{lt}, \theta_{lt}(y_{lt}), w) + v_{lt} - u_{lt}, \ (\theta_{lt}(y_{lt}) = (\theta_{lt1}(y_{lt}), \theta_{lt2}(y_{lt}), \dots, \theta_{lt(p-1)}(y_{lt})) \in [0, \pi/2]^{p-1}) \\ \theta_{lti}(y_{lt}) = \text{arc}\cos(m_{lti}(\theta)/\Pi_{j=0}^{i-1}\sin\theta_{ltj}), \ (i = 1, 2, 3, \dots, p) \end{cases} \tag{10}$$

where $y_{lt}$ is output vector of unit $l$ in period $t$, and $y_{lt} = \left(y_{lt1}, y_{lt2}, y_{lt3}, \ldots, y_{ltp}\right)$ if there are $p$ kinds of outputs; $x_{lt}$ is input vector and $x_{lt} = \left(x_{lt1}, x_{lt2}, \ldots, x_{ltk}\right)$ if there are $k$ kinds of inputs.

This paper chooses C–D production function. So, the model for calculating efficiency of multiple-type outputs is as follows:

$$\begin{cases} \ln l(y_{lt}) = \ln f(x_{lt}, \theta_{lt}(y_{lt}), w) + v_{lt} - u_{lt}, \\ \quad (\theta_{lt}(y_{lt}) = (\theta_{lt1}(y_{lt}), \theta_{lt2}(y_{lt}), \ldots, \theta_{lt(p-1)}(y_{lt})) \in [0, \pi/2]^{p-1}) \\ \ln f(x_{lt}, \theta_{lt}(y_{lt}), w) = \beta_0 + \sum_1^K \beta_k \cdot \ln x_{ltk} \\ \qquad + \sum_1^{P-1} \beta_{lti} \cdot \ln\theta_{lti}(y_{lt}) + v_{lt} - u_{lt} \\ \theta_{lti}(y_{lt}) = \arccos(m_{lti}(\theta)/\Pi_{j=0}^{i-1} \sin\theta_{ltj}), \ (i = 1, 2, 3, \ldots, p-1) \\ u_{lt} = (u_l \exp(-\eta(t-T))), \ (l = 1, 2, \ldots, L; t = 1, 2, \ldots, T) \end{cases} \tag{11}$$

In addition, when measuring single-type output, this study adopts the single-type output SFA model developed by Battese and Coelli (1992). The models for calculating the efficiency of single-type output are as follows:

$$\begin{cases} \ln l(y_{lt}) = \ln f(x_{lt}, \theta_{lt}(y), w) + v_{lt} - u_{lt}, \ (\theta_{lt}(y) = (\theta_{lt1}(y), \theta_{lt2}(y), \ldots, \theta_{lt(p-1)}(y)) \in [0, \pi/2]^{p-1}) \\ \theta_{lti}(y) = \arccos(m_{lti}(\theta)/\Pi_{j=0}^{i-1} \sin\theta_{ltj}), \ (i = 1, 2, 3, \ldots, p-1) \end{cases}, \tag{12}$$

where $y_{lt}$ is a scalar which represents one kind of special output of unit $l$ in period $t$. $x_{lt}$ is input vector and $x_{lt} = \left(x_{lt1}, x_{lt2}, \ldots, x_{ltk}\right)$ if there are $k$ kinds of inputs.

It should be noted that the formulation of SFA includes two functions. One is the frontier function for efficiency estimation and the other is the inefficiency function for exploring technical inefficiency factors. Battese and Coelli (1992) applied maximum likelihood estimator to estimate the parameter of frontier function and then calculated $\sigma$ and $\gamma$ based on the two formulas: $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\left(\sigma_v^2 + \sigma_u^2\right)$. When there is no technical inefficiency, e.g., $\gamma = 0$, the ordinary OLS method is appropriate. Therefore, we need to test whether $\gamma$ is equal to 0 or not. The SFA is suitable for the study only when $\gamma \neq 0$ is significant.

In the implementation of our analyses, we follow previous studies (e.g., Chen and Kou 2014; Schilling and Phelps 2007; Zhang et al. 2019) and calculate models lagging for 0, 1, 2 and 3 years to reduce simultaneity problems and enhance the robustness of regression results. Then, this paper will implement twenty SFA models for five kinds of R&D outputs.

## Variables and data source

Since research institutes, as a typical R&D organization, are mainly devoted to R&D activities, it is more appropriate to use research institutes as our research sample. Besides, the research institutes play a critical role in regional S&T activities in China (Zhang et al. 2019), and this study adopts the region-level panel dataset of China's research institutes to implement our analyses. The data cover twenty nine provinces. Eleven of them belong to eastern and coastal regions, i.e., Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan and Hebei. The rest eighteen provinces are inland regions, including Chongqing, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Sichuan, Guizhou, Yunnan, Shannxi, Gansu, Ningxia and Xinjiang.

Due to insufficient data, our sample does not include Tibet, Qinghai, Taiwan, Hong Kong and Macao.

R&D inputs and outputs are two indispensable variables of measuring regional R&D efficiency. Specifically, R&D manpower and knowledge stock are significantly related to R&D inputs (Guan et al. 2016; Wang and Huang 2007). To measure R&D manpower, extant studies usually take the full-time equivalent R&D personnel (e.g., Chen and Kou 2014) or the number of real R&D personnel (e.g., Chen and Guan 2012; Fu and Yang 2009) as a proxy. To ensure the data availability and consistence with the gender structure of R&D personnel, this study adopts the number of real R&D personnel to measure the R&D manpower input. With respect to the knowledge stock, it is almost impossible to count it precisely. Therefore, many researchers take R&D capital stock as a substitution of R&D knowledge stock (Beneito and Sanchis 2015; Goto and Suzuki 1989; Hall and Mairesse 1995). To calculate R&D capital stock, many studies adopt the capital inventory method proposed by Griliches (1979), which is proved to be effective (Goto and Suzuki, 1989; Hall and Mairesse, 1995). Therefore, this study takes a capital inventory method to calculate R&D capital stock in the base period. The formula is presented below.

$$K_{it} = (1 - \delta_{it})K_{it-1} + R_{it}, \quad (i = 1, 2, \dots, N; t = 1, 2, \dots, T), \tag{13}$$

where $K_{it}$ denotes the R&D capital stock of object $i$ in period $t$; $K_{it-1}$ is the R&D capital stock of object $i$ in period $t-1$; $\delta$ denotes the rate of depreciation; $R_{it}$ is the R&D capital input of object $i$ in period $t$.

To calculate $K_{it}$, two issues need to be solved: how to calculate R&D capital stock in the base period and how to deduct inflation of R&D capital. To solve the first issue, this study adopts the method used by Goto and Suzuki (1989), which assumes the average growing rate of R&D capital inputs is constant when $K_{it-1}$ is calculated. The formula is presented below:

$$K_{i0} = R_{i0}/(g + \delta), \tag{14}$$

where $g$ denotes the average growing rate of R&D capital inputs; $\delta$ is the rate of depreciation; $R_{i0}$ denotes the R&D capital stock in the base period. The parameter $g$ can be calculated by using R&D capital inputs subtracting the labor cost, which is contained in R&D capital inputs after eliminating inflation. With the approach above, this study can gain the R&D capital stock in the base period. As for the second issue, the inflation index can be calculated by the sum weighted consumption index and the fixed capital index, which is easy to eliminate inflation in R&D capital.

With respect to the R&D outputs, researchers mainly use either the invention patents or the revenues of new products to measure them (Cheung and Ping 2004; De 2013; Hunt et al. 2013; Jung and Ejermo 2014; Siegel et al. 2003a, b). Since research institutes are the critical knowledge creators and have long been serving as important sources of scientific and technical knowledge (Zhang et al. 2019), they not only produce scientific research outputs (e.g., S&T papers and books) but also have technology development outputs (e.g., invention patents, and standards). Although non-codified knowledge and other informal information are also the outputs of research institutes, their data source is unavailable in many cases (Zhang et al. 2016). For this reason, this study only adopts the available and tangible R&D outcomes with codified knowledge, including S&T papers (PAP), S&T books (BOO), invention patents (PAT), and national/industrial standards (STA). Among the four types R&D outputs, the first two are the typical scientific research outputs, while the latter two usually result from technology development activities. These four R&D outputs are measured by the absolute number respectively. It should be noted that the invention patents (PAT) is measured by the number of invention patent applications rather than invention patent grants since the invention patent applications are less vulnerable to the working efficiency than invention patent grants and thus this indicator can reflect the real R&D outputs more objectively (Yue 2008).

The core variable in this study is the gender structure of R&D personnel (GENDER). Previous research often measured the gender structure or gender diversity by computing the proportion of women in R&D personnel of per team/institute (e.g., Adusei and Obeng 2019; Nielsen and Börjeson 2019; Turner 2009; Ye et al. 2019). In this paper, we follow previous studies and measure gender structure by computing the ratio of the number of female R&D personnel to the total number of R&D personnel.

Most variables are uncontrollable in the R&D process (Chen and Kou 2014), which maybe promote or hinder R&D efficiency. This study follows previous region-level studies (Fritsch and Slavtchev 2007; Furman et al. 2002; Li 2009) and controls some variables that may affect the R&D efficiency. Specifically, the department structure of R&D personnel (measured by the ratio of the number of R&D personnel in basic research department ($DEP_1$) to the number of R&D personnel in applied research department ($DEP_2$)) is controlled. As Kim and Oh (2002) argued, the characteristics of R&D researchers should be considered in measuring R&D performance because members get involved in different types of R&D activities, which can bring different efficiency scores. So, the variables $DEP_1$ and $DEP_2$ likely affect the R&D efficiency and should be controlled. Furthermore, some social-economic factors, such as GDP per person (PGDP) and education input per person (PEDU), need to be included when we examine the effect of gender structure on R&D efficiency. According to Wang (2007), the environmental variables should be taken into account as the R&D performance is likely affected by many social-economic factors. So, we follow previous studies and control PGDP and PEDU in order to distinguish the external effects from net R&D efficiency. In terms of the R&D efficiency discrepancy between regions, this paper considers the geographical factor. This study introduces a dummy variable, Eastern and Coastal Region (ECR), and sets its value as 1 if one region belongs to eastern and coastal regions with relative developed economy and industry conditions. The definition and calculation of variables are presented in Table 1.

The data of most variables are collected from *China Statistical Yearbook on Science and Technology*. The data of some variables, e.g., education investment and GDP, are collected from *China Statistical Yearbook*. The data in this study are traced back to year 2009 based on their availability. The descriptive statistic of the panel data used in this study is listed in Table 2, which includes all R&D input and output variables, the gender structure of R&D personnel variable and other important control variables. There are in total 261 sets of observations from 2009 to 2017 (see "Appendix 1").

In order to examine whether there is multi-collinearity problem among explanatory variables, we carry out correlation analysis (see the results in Table 3). Clearly, we find that most correlation coefficients between explanatory variables are below the threshold value 0.7, suggesting there may not be serious multi-collinearity problem. Even so, we implement a robustness check by calculating the variance inflation factors (VIFs) of explanatory variables (Anand et al. 2010), which shows the values of all VIFs fall below the threshold value 10, suggesting the multi-collinearity does not seem to be a problem for our research model (Blais 2003).

**Table 1** Definition and measure of variables

| Variables | Sign | Definition and measure |
|---|---|---|
| S&T papers | PAP | Number of papers published on foreign journals yearly |
| S&T books | BOO | Number of S&T books published yearly |
| Invention patent applications | PAT | Number of invent patent application yearly |
| National/industrial standards | STA | Number of national or industrial criteria made yearly |
| Norm of multiple R&D output | Norm | The norm of PAP, BOO, PAT and STA |
| R&D labor input | $L$ | Number of R&D personnel |
| R&D capital input | $K$ | The stock of R&D capital |
| Gender structure of R&D personnel | GENDER | Proportion of female R&D personnel to total R&D personnel |
| Proportion of R&D personnel being engaged in basic research | $DEP_1$ | Proportion of R&D personnel being engaged in basic research to total R&D personnel |
| Proportion of R&D personnel being engaged in applied research | $DEP_2$ | Proportion of R&D personnel being engaged in applied research to total R&D personnel |
| GDP per person | PGDP | GDP divided by the number of population |
| Education investment per person | PEDU | Education fee divided by the number of population |
| Easter and costal region | ECR | It's 1 if the district belongs to eastern and costal region (ECR) |

**Table 2** Descriptive statistic of variables

| Variables | Average value | SD | Minimum | Maximum |
|---|---|---|---|---|
| LnNorm | 6.740 | 1.349 | 2.221 | 10.969 |
| LnPAP | 6.304 | 1.709 | 0.000 | 10.952 |
| LnBOO | 4.502 | 0.915 | 1.099 | 7.836 |
| LnPAT | 6.009 | 1.359 | 1.946 | 9.428 |
| LnSTA | 3.846 | 1.202 | 0.000 | 8.098 |
| Ln$L$ | 9.024 | 1.004 | 5.956 | 11.690 |
| Ln$K$ | 13.709 | 1.283 | 9.524 | 17.075 |
| GENDER | 0.325 | 0.050 | 0.039 | 0.444 |
| $DEP_1$ | 0.171 | 0.092 | 0.011 | 0.432 |
| $DEP_2$ | 0.349 | 0.086 | 0.116 | 0.657 |
| Ln(PGDP) | 10.226 | 0.438 | 9.240 | 11.269 |
| Ln(PEDU) | 7.354 | 0.387 | 6.539 | 8.402 |

## Empirical results

This section will present statistical results for twenty SFA models for five types of R&D outputs with the time lag of 0, 1, 2 and 3 years, respectively, to display how the gender structure of R&D personnel affects the R&D efficiency (see Tables 4, 5, 6, 7, 8). For all models, the $\gamma \neq 0$ is significant, which confirms the existence of technical R&D inefficiency and the justification for adopting SFA estimation.

**Table 3** Pearson/Spearman correlation matrix ($n=261$)

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. Ln norm | 1.000*** | | | | | | |
| 2. Ln PAP | 0.860*** | 1.000*** | | | | | |
| 3. Ln BOO | 0.749*** | 0.694*** | 1.000*** | | | | |
| 4. Ln PAT | 0.800*** | 0.731*** | 0.646*** | 1.000*** | | | |
| 5. Ln STA | 0.617*** | 0.528*** | 0.612*** | 0.649*** | 1.000*** | | |
| 6. Ln *K* | 0.796*** | 0.635*** | 0.541*** | 0.706*** | 0.713*** | 1.000*** | |
| 7. Ln *L* | 0.687*** | 0.632*** | 0.644*** | 0.688*** | 0.714*** | 0.670*** | 1.000*** |
| 8. Gender | −0.014 | −0.011 | 0.114* | −0.114* | −0.037 | −0.215*** | −0.249*** |
| 9. $DEP_1$ | 0.176*** | 0.231*** | 0.073 | 0.015 | 0.062 | −0.132** | −0.147** |
| 10. $DEP_2$ | −0.043 | −0.085 | 0.036 | 0.012 | 0.075 | 0.033 | −0.014 |
| 11. PGDP | 0.446*** | 0.362*** | 0.473*** | 0.526*** | 0.596*** | 0.452*** | 0.456*** |
| 12. PEDU | 0.516*** | 0.414*** | 0.391*** | 0.481*** | 0.478*** | 0.292*** | 0.261*** |
| 13. ECR | 0.364*** | 0.356*** | 0.378*** | 0.364*** | 0.355*** | 0.244*** | 0.215*** |
| **Variable** | **8** | **9** | **10** | **11** | **12** | **13** | |
| 8. Gender | 1.000*** | | | | | | |
| 9. $DEP_1$ | 0.353*** | 1.000*** | | | | | |
| 10. $DEP_2$ | 0.008 | −0.132** | 1.000*** | | | | |
| 11. PGDP | 0.049 | −0.194*** | 0.279*** | 1.000*** | | | |
| 12. PEDU | 0.312*** | 0.241*** | −0.004 | 0.558*** | 1.000*** | | |
| 13.ECR | 0.124** | 0.030 | 0.255*** | 0.660*** | 0.331*** | 1.000*** | |

Pearson's correlation coefficients are shown in the lower triangle, while Spearman's rank correlations appear in the higher triangle

***, ** and * denotes the significant level of 1%, 5% and 10% respectively

## Empirical results for multiple types of R&D outputs

To explore the effect of gender structure of R&D personnel on the comprehensive R&D efficiency in the case of multiple types of R&D outputs, the Maximum Likelihood Ratio is constructed between two kinds of models. One contains all considered elements, while the other just excludes gender structure of R&D personnel variable. The empirical results denote whether the gender structure of R&D personnel significantly affects R&D efficiency in terms of multiple-type outputs (Table 4).

The estimation results shown in Model 1–8 of Table 5 report that the values of $\sigma^2$ and $\gamma$ are significantly different from zero, indicating the existence of technical inefficiency. This means the SFA modeling is suitable for this study. In addition, two random variables ln*K* and ln*L* exhibit a positive and statistically significant effect, indicating that the more research investments result in the more R&D outputs. This finding is consistent with Griliches (1979). In the models 2, 3 and 4 that contain the gender structure of R&D personnel with time lag of 1, 2 and 3 years, respectively, the coefficient of the gender structure of R&D personnel is positive and significant. Clearly, the proportion of female R&D personnel to all R&D personnel is positively related to the technological inefficiency item of SFA model, indicating the gender structure of R&D personnel is negatively related to the comprehensive R&D efficiency. In other words, the higher proportion of female R&D

**Table 4** The effect of the gender structure on the comprehensive R&D efficiency for multiple types of R&D outputs

| Coefficients | No time lag | | Lag for 1 year | | Lag for 2 years | | Lag for 3 years | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
| *Frontier function* | | | | | | | | |
| Constant | −2.513*** | (−6.132) | −1.637*** | (−4.278) | −1.752*** | (−2.516) | −0.736 | (−1.492) |
| ln*L* | 0.483*** | (3.141) | 0.978*** | (8.463) | 1.080*** | (3.989) | 1.315*** | (10.071) |
| ln*K* | 0.373*** | (3.318) | −0.020 | (−0.211) | −0.026 | (−0.125) | −0.293*** | (−2.597) |
| *Inefficiency function* | | | | | | | | |
| Constant 1 | 11.742*** | (4.243) | 10.007*** | (6.592) | 1.289 | (1.207) | 8.306*** | (4.180) |
| Gender | 2.251 | (1.415) | 2.236*** | (2.532) | 0.733* | (0.722) | 2.896*** | (2.486) |
| $DEP_1$ | −4.046*** | (−2.638) | −2.633*** | (−3.691) | −0.975 | (−0.992) | −3.151*** | (−3.396) |
| $DEP_2$ | 1.220 | (1.484) | 0.551 | (1.352) | 0.481 | (0.495) | 0.395 | (0.709) |
| Ln(PGDP) | −0.323 | (−0.957) | −0.297 | (−1.737) | 0.575*** | (3.371) | −0.162 | (−0.711) |
| Ln(PEDU) | −1.132** | (−2.214) | −0.923*** | (−3.942) | −0.842*** | (−2.910) | −0.922*** | (−2.697) |
| ECR | −0.446 | (−1.864) | −0.278*** | (−2.690) | −0.427*** | (−3.259) | −0.411*** | (−2.706) |
| $\sigma^2$ | 0.404*** | (4.027) | 0.129*** | (6.585) | 0.160*** | (4.665) | 0.120*** | (4.973) |
| $\gamma$ | 0.947 | (34.982) | 0.881*** | (13.529) | 1.000*** | (6.448) | 0.861*** | (8.153) |
| Ols-log | −130.434 | | −101.755 | | −77.913 | | −56.431 | |
| Log | −83.079 | | −36.217 | | −51.831 | | −16.307 | |
| Log | −73.688 | | −43.024 | | −30.128 | | −21.393 | |
| LR | 94.709 | | 131.076 | | 52.164 | | 80.247 | |

***, ** and * denotes the significant level of 1%, 5% and 10% respectively

**Table 5** The effect of the gender structure of R&D personnel on R&D efficiency in the case of S&T papers as R&D output

| Coefficients | No time lag | | Lag for 1 year | | Lag for 2 years | | Lag for 3 years | |
|---|---|---|---|---|---|---|---|---|
| | Model 5 | | Model 6 | | Model 7 | | Model 8 | |
| *Frontier function* | | | | | | | | |
| Constant | 0.847*** | (3.356) | 2.049*** | (5.797) | 1.490* | (2.282) | 2.322*** | (4.503) |
| ln*L* | 0.541*** | (5.248) | 0.854*** | (9.498) | 0.732*** | (4.521) | 0.945*** | (7.677) |
| ln*K* | 0.224*** | (2.629) | −0.060 | (−0.720) | 0.059 | (0.394) | −0.132 | (−1.135) |
| *Inefficiency function* | | | | | | | | |
| Constant | 0.212 | (0.145) | 1.653 | (1.739) | 1.361 | (1.353) | 1.765 | (1.642) |
| Gender | −2.228*** | (−2.347) | −0.619* | (−0.692) | −1.281* | (−1.211) | −1.288* | (−1.563) |
| $DEP_1$ | −2.513*** | (−3.668) | −2.173*** | (−4.318) | −2.445*** | (−5.427) | −2.023*** | (−2.483) |
| $DEP_2$ | 1.180*** | (2.626) | 1.048*** | (3.156) | 1.243*** | (3.323) | 0.717 | (1.237) |
| Ln(PGDP) | 0.384* | (1.979) | 0.193 | (1.361) | 0.233 | (1.267) | 0.282 | (1.017) |
| Ln(PEDU) | −0.415* | (−1.965) | −0.387*** | (−2.357) | −0.397 | (−1.729) | −0.490 | (−1.233) |
| ECR | −0.513*** | (−3.937) | −0.425*** | (−5.800) | −0.480*** | (−4.971) | −0.376*** | (−2.836) |
| $\sigma^2$ | 0.132*** | (6.349) | 0.083*** | (5.982) | 0.093*** | (4.961) | 0.080*** | (3.503) |
| $\gamma$ | 0.900*** | (6.720) | 1.000*** | (> 100) | 1.000*** | (> 100) | 1.000*** | (> 100) |
| Ols-log | −90.307 | | −64.544 | | −51.569 | | −38.671 | |
| Log | −40.272 | | −10.331 | | −5.284 | | −2.979 | |
| LR | 105.606 | | 108.426 | | 92.569 | | 71.384 | |

***, ** and * denotes the significant level of 1%, 5% and 10% respectively

**Table 6** The effect of the gender structure of R&D personnel on R&D efficiency in the case of S&T books as R&D output

| Coefficients | No time lag | | Lag for 1 year | | Lag for 2 years | | Lag for 3 years | |
|---|---|---|---|---|---|---|---|---|
| | Model 9 | | Model 10 | | Model 11 | | Model 12 | |
| *Frontier function* | | | | | | | | |
| Constant | − 1.990*** | (− 3.054) | − 0.299 | (− 0.474) | − 0.253 | (− 0.540) | 0.532 | (0.982) |
| ln*L* | 0.333* | (1.970) | 0.973*** | (4.682) | 0.890*** | (4.140) | 1.062*** | (4.255) |
| ln*K* | 0.319*** | (2.439) | − 0.179 | (− 1.103) | − 0.138 | (− 0.830) | − 0.305 | (− 1.552) |
| *Inefficiency function* | | | | | | | | |
| Constant | 2.600 | (1.616) | 2.185 | (1.243) | 1.087 | (1.067) | 2.686 | (1.787) |
| Gender | − 3.531*** | (− 3.304) | − 2.676* | (− 1.323) | − 0.759* | (− 0.781) | − 0.578* | (− 0.597) |
| $DEP_1$ | − 0.777 | (− 1.306) | − 1.040 | (− 1.341) | − 0.612 | (− 0.700) | − 1.473 | (− 1.575) |
| $DEP_2$ | − 0.043 | (− 0.088) | 0.783 | (1.454) | 0.448 | (0.499) | − 0.240 | (− 0.343) |
| Ln(PGDP) | 0.298 | (1.353) | 0.296 | (1.580) | 0.339 | (1.228) | 0.284 | (0.948) |
| Ln(PEDU) | − 0.497** | (− 2.001) | − 0.381 | (− 1.384) | − 0.400 | (− 0.991) | − 0.507 | (− 1.175) |
| ECR | − 0.367*** | (− 3.094) | − 0.536*** | (− 2.980) | − 0.389*** | (− 3.426) | − 0.250*** | (− 2.519) |
| $\sigma^2$ | 0.294*** | (9.420) | 0.243*** | (6.364) | 0.269*** | (5.364) | 0.261*** | (4.461) |
| $\gamma$ | 0.005 | (0.004) | 1.000*** | (36.842) | 1.000*** | (> 100) | 1.000*** | (> 100) |
| Ols-log | − 164.388 | | − 125.619 | | − 100.475 | | − 74.646 | |
| Log | − 140.284 | | − 100.025 | | − 83.772 | | − 60.533 | |
| LR | 48.208 | | 51.190 | | 33.406 | | 28.226 | |

***, ** and * denotes the significant level of 1%, 5% and 10% respectively

**Table 7** The effect of the gender structure of R&D personnel on R&D efficiency in the case of invention patent applications as R&D output

| Coefficients | No time lag | | Lag for 1 year | | Lag for 2 years | | Lag for 3 years | |
|---|---|---|---|---|---|---|---|---|
| | Model 13 | | Model 14 | | Model 15 | | Model 16 | |
| *Frontier function* | | | | | | | | |
| Constant | − 3.290*** | (− 8.052) | − 2.178*** | (− 4.851) | − 2.017*** | (− 4.109) | − 1.800*** | (− 2.449) |
| ln*L* | 0.227** | (2.072) | 0.746*** | (5.573) | 0.881*** | (6.225) | 1.028*** | (4.575) |
| ln*K* | 0.599*** | (6.808) | 0.185 | (1.735) | 0.089 | (0.810) | − 0.020 | (− 0.134) |
| *Inefficiency function* | | | | | | | | |
| Constant | 9.357*** | (5.219) | 7.548*** | (4.567) | 5.899*** | (3.410) | 3.870* | (1.828) |
| Gender | 1.079 | (1.047) | 2.120** | (2.255) | 2.457*** | (2.386) | 2.998*** | (2.407) |
| $DEP_1$ | − 2.667*** | (− 4.100) | − 2.685*** | (− 4.424) | − 2.653*** | (− 3.966) | − 2.305*** | (− 3.332) |
| $DEP_2$ | 0.999 ** | (2.041) | 0.846* | (1.895) | 1.071** | (2.172) | 1.069 | (1.371) |
| Ln(PGDP) | − 0.468*** | (− 2.302) | − 0.403** | (− 2.133) | − 0.327 | (− 1.618) | − 0.047 | (− 0.220) |
| Ln(PEDU) | − 0.537* | (− 1.853) | − 0.412 | (− 1.568) | − 0.329 | (− 1.105) | − 0.506 | (− 1.396) |
| ECR | − 0.293*** | (− 2.349) | − 0.370*** | (− 3.392) | − 0.508*** | (− 4.220) | − 0.624*** | (− 3.120) |
| $\sigma^2$ | 0.197*** | (6.005) | 0.147*** | (6.165) | 0.125*** | (5.348) | 0.110*** | (3.075) |
| $\gamma$ | 0.835*** | (11.295) | 0.776*** | (6.333) | 0.675*** | (3.357) | 0.442 | (0.629) |
| Ols-log | − 136.680 | | − 104.848 | | − 78.594 | | − 55.839 | |
| Log | − 76.286 | | − 49.587 | | − 32.293 | | − 22.291 | |
| LR | 120.789 | | 110.523 | | 92.601 | | 67.095 | |

***, ** and * denotes the significant level of 1%, 5% and 10% respectively

**Table 8** The effect of the gender structure of R&D personnel on R&D efficiency in the case of national/industrial standards as R&D output

| Coefficients | No time lag | | Lag for 1 year | | Lag for 2 years | | Lag for 3 years | |
|---|---|---|---|---|---|---|---|---|
| | Model 17 | | Model 18 | | Model 19 | | Model 20 | |
| *Frontier function* | | | | | | | | |
| Constant | −1.119 | (−1.706) | −0.949 | (−1.728) | −0.074 | (−0.074) | 0.961 | (0.805) |
| ln*L* | 0.452 | (1.789) | 1.273*** | (4.435) | 0.852*** | (2.832) | 1.257*** | (3.665) |
| ln*K* | 0.240 | (1.166) | −0.335 | (−1.458) | −0.097 | (−0.376) | −0.436 | (−1.621) |
| *Inefficiency function* | | | | | | | | |
| Constant | 14.537*** | (6.572) | 12.976*** | (7.997) | 14.915*** | (6.835) | 15.647*** | (7.011) |
| Gender | 2.512*** | (2.500) | 2.302** | (2.145) | 2.323* | (1.106) | 1.442* | (0.279) |
| $DEP_1$ | −3.218*** | (−3.770) | −2.546*** | (−2.576) | −3.194*** | (−2.471) | −2.907*** | (−2.973) |
| $DEP_2$ | −0.283 | (−0.342) | −0.308 | (−0.366) | 0.337 | (0.284) | −0.815 | (−1.246) |
| Ln(PGDP) | −0.379 | (−1.226) | −0.556 | (−1.734) | −0.516 | (−0.984) | −0.620* | (−1.877) |
| Ln(PEDU) | −1.225*** | (−3.185) | −0.789* | (−1.953) | −1.108* | (−1.913) | −0.950** | (−2.225) |
| ECR | 0.067 | (0.357) | 0.292 | (1.449) | 0.114 | (0.748) | 0.327* | (1.807) |
| $\sigma^2$ | 0.540*** | (7.773) | 0.525*** | (5.344) | 0.474*** | (7.579) | 0.337*** | (6.629) |
| $\gamma$ | 1.000*** | (> 100) | 1.000*** | (> 100) | 1.000*** | (> 100) | 1.000*** | (> 100) |
| Ols-log | −223.805 | | −179.905 | | −147.145 | | −99.274 | |
| Log | −18.997 | | −152.288 | | −120.667 | | −75.223 | |
| LR | 67.658 | | 55.234 | | 52.958 | | 48.102 | |

***, ** and * denotes the significant level of 1%, 5% and 10% respectively

personnel results in the lower R&D efficiency. This denotes that the comprehensive R&D efficiency of female researchers is lower than that of the male researchers.

## Empirical results for each single type of R&D outputs

The previous section proves that there indeed exists a gender discrepancy between the male and female in R&D efficiency, but the finding is based on the measurement of multiple types of R&D outputs, which might cover up the gender discrepancy in different kinds of R&D outputs with different characteristics. Therefore, it is necessary to further investigate the impact of gender structure on R&D efficiency from the perspective of each single type of R&D output.

### S&T papers

This section will examine the effect of the gender structure of R&D personnel on the R&D efficiency in the case of S&T papers as R&D output, and the regression results are presented in Table 5.

Based on the estimation results shown in models 5–8, we can find that the values of $\sigma^2$ and $\gamma$ are not zero, indicating the existence of technical inefficiency. Therefore, the SFA is suitable for this study (Battese and Coelli 1995). Moreover, two random variables ln$K$ and ln$L$ exhibit a positive and statistically significant effect on S&T papers as R&D output. As shown in the models 5, 6, 7 and 8, we find that the gender structure is negatively and significantly related to the technological inefficiency item of SFA model with the time-lag of 1–3 years, which means that the higher proportion of female R&D personnel results in the lower R&D inefficiency. In other words, the female researchers have a higher R&D efficiency in publishing S&T papers than their male counterparts.

#### S&T books

This section will examine the effect of the gender structure of R&D personnel on the R&D efficiency in the case of S&T books as R&D output, and the regression results are presented in Table 6.

As shown in the models 9, 10, 11 and 12, we find that the gender structure of R&D personnel is negatively and significantly related to the technological inefficiency item of SFA model. This means that the larger proportion of female researchers can reduce the R&D inefficiency. In other words, the gender structure of R&D personnel is positively related to the R&D efficiency, indicating the female researchers are more efficient than their male counterparts in publishing S&T books.

#### Invention patent applications

This section explores whether the gender structure of R&D personnel affects R&D efficiency in the case of invention patent applications as R&D output, and the regression results are presented in Table 7.

As shown by the models 14, 15 and 16, we find that the coefficient of the gender structure is positively and significantly related to the technological inefficiency item of SFA with the time-lag of 1–3 years, suggesting the larger the proportion of female researchers is, the lower the R&D efficiency is. In other words, there is a negative relationship between the gender structure of R&D personnel and R&D efficiency in the case of invention patent applications as R&D output, indicating the male researchers have a higher efficiency than female researchers in conducting invention patent applications.

#### National/industrial standards

The regression result regarding the effect of the gender structure of R&D personnel on R&D efficiency in the case of national/industrial standards as R&D output is presented in Table 8.

As shown in the models 17, 18, 19 and 20 where the gender structure of R&D personnel is included, we find that the coefficient of the gender structure of R&D personnel is positive and significant. This indicates that the larger the proportion of female researchers is, the higher the R&D inefficiency is. That is to say, the gender structure of R&D personnel is negatively related to the R&D efficiency, suggesting the male researchers are more efficient than their female researchers in designing national/industrial standards.

### Robustness checks

It should be noted that the gender diversity likely suffers from an endogeneity problem as it is possible outcome of the research institutes which are seeking and hiring human resources on the basis of competencies and talents rather than on the basis of gender distribution. In order to further eliminate the potential endogeneity, we take some actions as follows. Firstly, we follow Alonso-Borrego and Arellano (1999) and introduce the time lags between the explanatory variable (gender diversity) and the dependent variable (R&D efficiency) to address a logical question (Who influences whom?) between them. We calculate models lagging for 1, 2 and 3 years to capture the lag effect and thus eliminate the endogeneity. Secondly, we attempt to use an instrumental variable to solve the potential endogeneity. Specifically, we follow Almor et al. (2019) and use the territorial index, namely, the eastern region and the central and western region in China, as an instrumental variable because it is an impersonal proxy for reflecting the character of public/private agents operating in a particular region. The MLE is used to run a regression, and the results are reported in Table 10 of "Appendix 2". According to the regression results with the instrumental variable, we can find that the coefficients are in line with the research findings reported in Sect. "Empirical results for each single type of R&D outputs" above in terms of sign and significance. This suggests our research findings are robustness.

## Conclusions and discussions

A significant amount of studies explore the statistical differences between females and males from the social and biological perspectives (De 2013; Hunt et al. 2013; Jung and Ejermo 2014; McWhirter 1997). However, little attention has been paid to the gender differences in R&D efficiency. Further, it is far from clear about the impact of the gender structure of R&D personnel on the R&D efficiency, especially in the case of different types of R&D outputs. In this study, we take into account of four types of R&D outputs respectively and comprehensively, and apply multiple-R&D-output-SFA as well as single-R&D-output-SFA to explore this issue. In this way, we make some comparisons on statistical differences between female and male R&D personnel in the R&D efficiency score, which can provide multi-aspect evidence for the association between gender structure and R&D efficiency in the S&T field.

The findings suggest that the gender gap of R&D efficiency indeed exists. Specifically, by adopting the single-R&D-output-SFA model where the R&D efficiency is measured by one single type of R&D output, we find that the higher proportion of female researchers is conducive to the higher R&D efficiency when it is measured by the number of S&T books and national/industrial standards as R&D output. Nevertheless, the higher proportion of female researchers may not result in the higher/lower R&D efficiency when it is measured by the number of S&T papers and invention patent applications as R&D output. In addition, we find that the higher proportion of male researchers has an additional effect on the comprehensive R&D efficiency by adopting the multiple-R&D-output-SFA model where the R&D efficiency is measured by four types of R&D outputs, simultaneously. Keeping the proportion of female researchers within a certain range is also conducive to the improvement of R&D efficiency.

This study has important theoretical and methodological implications. First, it contributes to our better understanding on the internal determinants of R&D efficiency score. In contrast with most of extant literature which usually focuses on the effects of external (environment) factors (e.g., Guan et al. 2016; Fritsch and Slavtchev 2007, 2010), this paper explores the effect of an important internal factor (i.e., gender structure of R&D personnel) on R&D efficiency. Second, this paper enriches the literature about the gender gap in R&D performance. Different with the extant literature (De 2013; Hunt et al. 2013; Jung and Ejermo 2014; McWhirter 1997) which reveals the gender gap in R&D output performance, e.g., patenting and publishing, our study provides evidence for the gender gap in the R&D input–output process performance (i.e., R&D efficiency).

This study also has important policy implications. The findings of this study can be regarded a guidance to the structure and task design of research institutes to improve their R&D efficiency from the gender perspective. Different types of research projects should consider a more appropriate gender of researchers. For the research task with more scientific characteristics, female researchers are more appropriate, while for that with more technological characteristics, male researchers are more needed from the efficiency perspective.

One limitation is that the macro-level data constraint this study from digging into some interesting research questions, such as the relationship between heterosexual collaboration advantages and R&D efficiency, as well as the relationship between ages and R&D efficiency and so on. Secondly, the factors that might incur the gender gap in R&D efficiency, such as education background, marital status and age, deserve further exploration in future studies. Thirdly, due to the data limitation at the province-level, we cannot split up gender composition according to researchers' tasks (basic and applied research) when investigating the R&D efficiency discrepancy between female and male personnel. Future studies should collect more indicators and data to cope with this limitation when exploring the link between gender structure and R&D efficiency. Last but not least, our study argues that the gender diversity of R&D teams is an important internal factor influencing R&D efficiency, neglecting an inverse effect between them. In fact, the R&D output productivity may be an antecedent promoting the gender diversity of R&D teams. This topic should be further explored in future studies.

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## Appendix 1: The number of research institutes from each region in China

Based on *China Statistical Yearbook on Science and Technology*, we manually collected the number of research institutes in each province of China from 2009 to 2017, which are presented in Table 9 as follows.

**Table 9** The number of research institutes from each region in China from 2009 to 2017

| Year | Province | Amount | Year | Province | Amount | Year | Province | Amount |
|---|---|---|---|---|---|---|---|---|
| 2009 | Beijing | 353 | 2010 | Beijing | 370 | 2011 | Beijing | 370 |
| 2009 | Tianjin | 69 | 2010 | Tianjin | 56 | 2011 | Tianjin | 58 |
| 2009 | Hebei | 74 | 2010 | Hebei | 75 | 2011 | Hebei | 75 |
| 2009 | Shanxi | 171 | 2010 | Shanxi | 172 | 2011 | Shanxi | 170 |
| 2009 | Inner Mongolia | 97 | 2010 | Inner Mongolia | 97 | 2011 | Inner Mongolia | 95 |
| 2009 | Liaoning | 169 | 2010 | Liaoning | 167 | 2011 | Liaoning | 166 |
| 2009 | Jilin | 119 | 2010 | Jilin | 119 | 2011 | Jilin | 112 |
| 2009 | Heilongjiang | 188 | 2010 | Heilongjiang | 182 | 2011 | Heilongjiang | 179 |
| 2009 | Shanghai | 134 | 2010 | Shanghai | 136 | 2011 | Shanghai | 134 |
| 2009 | Jiangsu | 149 | 2010 | Jiangsu | 147 | 2011 | Jiangsu | 148 |
| 2009 | Zhejiang | 101 | 2010 | Zhejiang | 99 | 2011 | Zhejiang | 98 |
| 2009 | Anhui | 111 | 2010 | Anhui | 111 | 2011 | Anhui | 107 |
| 2009 | Fujian | 104 | 2010 | Fujian | 96 | 2011 | Fujian | 97 |
| 2009 | Jiangxi | 112 | 2010 | Jiangxi | 115 | 2011 | Jiangxi | 116 |
| 2009 | Shandong | 230 | 2010 | Shandong | 229 | 2011 | Shandong | 227 |
| 2009 | Henan | 125 | 2010 | Henan | 124 | 2011 | Henan | 121 |
| 2009 | Hubei | 157 | 2010 | Hubei | 153 | 2011 | Hubei | 152 |
| 2009 | Hunan | 132 | 2010 | Hunan | 129 | 2011 | Hunan | 130 |
| 2009 | Guangdong | 183 | 2010 | Guangdong | 186 | 2011 | Guangdong | 185 |
| 2009 | Guangxi | 119 | 2010 | Guangxi | 126 | 2011 | Guangxi | 124 |
| 2009 | Hainan | 30 | 2010 | Hainan | 30 | 2011 | Hainan | 31 |
| 2009 | Chongqing | 29 | 2010 | Chongqing | 28 | 2011 | Chongqing | 30 |
| 2009 | Sichuan | 161 | 2010 | Sichuan | 171 | 2011 | Sichuan | 171 |
| 2009 | Guizhou | 75 | 2010 | Guizhou | 75 | 2011 | Guizhou | 73 |
| 2009 | Yunnan | 97 | 2010 | Yunnan | 105 | 2011 | Yunnan | 105 |
| 2009 | Shaanxi | 116 | 2010 | Shaanxi | 116 | 2011 | Shaanxi | 114 |
| 2009 | Gansu | 104 | 2010 | Gansu | 107 | 2011 | Gansu | 109 |
| 2009 | Ningxia | 22 | 2010 | Ningxia | 22 | 2011 | Ningxia | 22 |
| 2009 | Xinjiang | 110 | 2010 | Xinjiang | 109 | 2011 | Xinjiang | 111 |
| Year | Province | Amount | Year | Province | Amount | Year | Province | Amount |
| 2012 | Beijing | 379 | 2013 | Beijing | 380 | 2014 | Beijing | 392 |
| 2012 | Tianjin | 58 | 2013 | Tianjin | 58 | 2014 | Tianjin | 60 |
| 2012 | Hebei | 76 | 2013 | Hebei | 76 | 2014 | Hebei | 77 |
| 2012 | Shanxi | 170 | 2013 | Shanxi | 164 | 2014 | Shanxi | 163 |
| 2012 | Inner Mongolia | 97 | 2013 | Inner Mongolia | 97 | 2014 | Inner Mongolia | 97 |
| 2012 | Liaoning | 165 | 2013 | Liaoning | 164 | 2014 | Liaoning | 166 |
| 2012 | Jilin | 111 | 2013 | Jilin | 109 | 2014 | Jilin | 111 |
| 2012 | Heilongjiang | 180 | 2013 | Heilongjiang | 178 | 2014 | Heilongjiang | 178 |
| 2012 | Shanghai | 136 | 2013 | Shanghai | 136 | 2014 | Shanghai | 138 |
| 2012 | Jiangsu | 148 | 2013 | Jiangsu | 143 | 2014 | Jiangsu | 144 |
| 2012 | Zhejiang | 101 | 2013 | Zhejiang | 101 | 2014 | Zhejiang | 102 |
| 2012 | Anhui | 105 | 2013 | Anhui | 108 | 2014 | Anhui | 104 |
| 2012 | Fujian | 95 | 2013 | Fujian | 93 | 2014 | Fujian | 102 |
| 2012 | Jiangxi | 117 | 2013 | Jiangxi | 116 | 2014 | Jiangxi | 118 |

**Table 9** (continued)

| Year | Province | Amount | Year | Province | Amount | Year | Province | Amount |
|---|---|---|---|---|---|---|---|---|
| 2012 | Shandong | 225 | 2013 | Shandong | 224 | 2014 | Shandong | 217 |
| 2012 | Henan | 118 | 2013 | Henan | 116 | 2014 | Henan | 119 |
| 2012 | Hubei | 151 | 2013 | Hubei | 149 | 2014 | Hubei | 138 |
| 2012 | Hunan | 130 | 2013 | Hunan | 132 | 2014 | Hunan | 132 |
| 2012 | Guangdong | 184 | 2013 | Guangdong | 186 | 2014 | Guangdong | 189 |
| 2012 | Guangxi | 123 | 2013 | Guangxi | 120 | 2014 | Guangxi | 121 |
| 2012 | Hainan | 31 | 2013 | Hainan | 31 | 2014 | Hainan | 30 |
| 2012 | Chongqing | 30 | 2013 | Chongqing | 31 | 2014 | Chongqing | 27 |
| 2012 | Sichuan | 170 | 2013 | Sichuan | 169 | 2014 | Sichuan | 172 |
| 2012 | Guizhou | 79 | 2013 | Guizhou | 78 | 2014 | Guizhou | 79 |
| 2012 | Yunnan | 103 | 2013 | Yunnan | 101 | 2014 | Yunnan | 110 |
| 2012 | Shaanxi | 111 | 2013 | Shaanxi | 111 | 2014 | Shaanxi | 113 |
| 2012 | Gansu | 107 | 2013 | Gansu | 107 | 2014 | Gansu | 107 |
| 2012 | Ningxia | 21 | 2013 | Ningxia | 21 | 2014 | Ningxia | 21 |
| 2012 | Xinjiang | 112 | 2013 | Xinjiang | 111 | 2014 | Xinjiang | 109 |
| Year | Province | Amount | Year | Province | Amount | Year | Province | Amount |
| 2015 | Beijing | 389 | 2016 | Beijing | 396 | 2017 | Beijing | 391 |
| 2015 | Tianjin | 60 | 2016 | Tianjin | 61 | 2017 | Tianjin | 61 |
| 2015 | Hebei | 79 | 2016 | Hebei | 80 | 2017 | Hebei | 80 |
| 2015 | Shanxi | 166 | 2016 | Shanxi | 165 | 2017 | Shanxi | 162 |
| 2015 | Inner Mongolia | 97 | 2016 | Inner Mongolia | 98 | 2017 | Inner Mongolia | 96 |
| 2015 | Liaoning | 161 | 2016 | Liaoning | 158 | 2017 | Liaoning | 159 |
| 2015 | Jilin | 109 | 2016 | Jilin | 106 | 2017 | Jilin | 104 |
| 2015 | Heilongjiang | 172 | 2016 | Heilongjiang | 154 | 2017 | Heilongjiang | 147 |
| 2015 | Shanghai | 137 | 2016 | Shanghai | 134 | 2017 | Shanghai | 132 |
| 2015 | Jiangsu | 142 | 2016 | Jiangsu | 135 | 2017 | Jiangsu | 133 |
| 2015 | Zhejiang | 101 | 2016 | Zhejiang | 101 | 2017 | Zhejiang | 98 |
| 2015 | Anhui | 102 | 2016 | Anhui | 100 | 2017 | Anhui | 100 |
| 2015 | Fujian | 100 | 2016 | Fujian | 102 | 2017 | Fujian | 99 |
| 2015 | Jiangxi | 118 | 2016 | Jiangxi | 117 | 2017 | Jiangxi | 114 |
| 2015 | Shandong | 218 | 2016 | Shandong | 204 | 2017 | Shandong | 198 |
| 2015 | Henan | 119 | 2016 | Henan | 122 | 2017 | Henan | 122 |
| 2015 | Hubei | 134 | 2016 | Hubei | 123 | 2017 | Hubei | 116 |
| 2015 | Hunan | 132 | 2016 | Hunan | 123 | 2017 | Hunan | 119 |
| 2015 | Guangdong | 189 | 2016 | Guangdong | 202 | 2017 | Guangdong | 199 |
| 2015 | Guangxi | 120 | 2016 | Guangxi | 118 | 2017 | Guangxi | 119 |
| 2015 | Hainan | 28 | 2016 | Hainan | 28 | 2017 | Hainan | 28 |
| 2015 | Chongqing | 27 | 2016 | Chongqing | 37 | 2017 | Chongqing | 31 |
| 2015 | Sichuan | 171 | 2016 | Sichuan | 170 | 2017 | Sichuan | 169 |
| 2015 | Guizhou | 81 | 2016 | Guizhou | 82 | 2017 | Guizhou | 76 |
| 2015 | Yunnan | 110 | 2016 | Yunnan | 114 | 2017 | Yunnan | 118 |
| 2015 | Shaanxi | 111 | 2016 | Shaanxi | 106 | 2017 | Shaanxi | 104 |
| 2015 | Gansu | 108 | 2016 | Gansu | 106 | 2017 | Gansu | 106 |
| 2015 | Ningxia | 21 | 2016 | Ningxia | 21 | 2017 | Ningxia | 20 |

**Table 9** (continued)

| Year | Province | Amount | Year | Province | Amount | Year | Province | Amount |
|---|---|---|---|---|---|---|---|---|
| 2015 | Xinjiang | 108 | 2016 | Xinjiang | 106 | 2017 | Xinjiang | 104 |

## Appendix 2: Robustness checks with instrumental variables

See Table 10.

**Table 10** Maximum likelihood estimation with instrumental variables

| Coefficients | GENDER_REGION | | | | |
|---|---|---|---|---|---|
| | R&D efficiency (multiple types of R&D outputs) | R&D efficiency (S&T papers as R&D output) | R&D efficiency (S&T books as R&D output) | R&D efficiency (invent patent application as R&D output) | R&D efficiency (national/industrial standards as R&D output) |
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| Gender | **0.8022**** | **−6.9669***** | **−1.7873*** | **4.3434**** | **1.8544*** |
| | (−0.4195) | (−2.2207) | (−1.2066) | (−1.6254) | (0.7063) |
| $DEP_1$ | 0.5198* | 0.3046 | −0.0228 | 0.4535 | −0.3662*** |
| | (1.7665) | (0.6271) | (−0.1138) | (1.1030) | (−2.6512) |
| $DEP_2$ | −0.2465 | 0.2023 | −0.1669 | −0.0866 | −0.0819 |
| | (−1.1004) | (0.5504) | (−0.9873) | (−0.2769) | (−0.6680) |
| lnPGDP | 0.2061 | 0.9504*** | 0.0895 | −0.0237 | −0.0383 |
| | (1.3263) | (3.7138) | (1.0168) | (−0.1080) | (−0.6396) |
| lnPEDU | −0.6411*** | −1.1439*** | −0.0676 | −0.5438** | −0.1389* |
| | (−4.1966) | (−4.4883) | (−0.6231) | (−2.5487) | (−1.7614) |
| ECR | −0.2861** | −0.5277** | −0.1108* | −0.1818 | −0.0084 |
| | (−2.1825) | (−2.5253) | (−1.8521) | (−0.9872) | (−0.2214) |
| Constant | 3.7973*** | 2.0402 | 0.5927 | 6.7304*** | 1.5260*** |
| | (2.7698) | (0.9260) | (0.7978) | (3.4137) | (3.0895) |
| Observations | 261 | 261 | 261 | 261 | 261 |

***, ** and * denotes the significant level of 1%, 5% and 10% respectively

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## Affiliations

**Mingting Kou[1] · Yi Zhang[2] · Yu Zhang[3] · Kaihua Chen[3] · Jiancheng Guan[4] · Senmao Xia[5]**

[1] Donglinks School of Economics and Management, University of Sciences and Technology Beijing, Beijing, China

[2] School of Management, Guangdong Ocean University, Zhanjiang, China

[3] Institutes of Innovation and Development, Chinese Academy of Sciences, Beijing, China

[4] School of Economics and Management, University of Chinese Academy of Sciences, Beijing, China

[5] School of Strategy and Leadership, Coventry University, Coventry CV1 5FB, UK