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How do executive excess compensation affect enterprise technological innovation: Evidence from a panel threshold model of chinese biopharmaceutical companies

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ABSTRACT

This study examines the levels of executive excess compensation (EEC) that stimulate the quality and efficiency of enterprise technology innovation (ETI). Using a behavioral agency perspective, we investigate how companies achieve superior ETI by providing sufficient incentives to motivate executives to perform to the best of their abilities. We use a panel threshold model based on a sample of Chinese-listed biopharmaceutical companies and find that: (1) providing an EEC between 0.0592 and 0.1907 significantly affects the promotion of ETI quality; (2) regarding ETI efficiency, executives generally do not receive the compensation that they deserve; and (3) the existing EEC has a weak negative impact on ETI efficiency, gradually disappearing as compensation increases. Heterogeneity analysis reveals that restricting EEC to the eastern area and strengthening the supervision of EEC in state-owned enterprises are effective measures for stimulating ETI. We advance the literature by providing guidance on compensation plans to companies in different regions.

1. Introduction

Enterprise technology innovation (ETI) is critical for firm survival and development because it is equipped with a sustainable competitive advantage (Cai et al., 2021). ETI refers to the implementation of a new product/service or introduction of new elements into a firm's existing production process or service operations (Azar and Ciabuschi, 2017). Although ETI often involves incremental innovations in organizations, such innovations are effective in restraining competition and generating significant economic returns that are constantly pursued by business establishments (Yigitcanlar et al., 2019). The importance of ETI in firms' long-term growth has been well acknowledged in innovation management literature (e.g., Biscotti et al., 2018). In particular, the pursuit of radical innovation (Ansari and Krop, 2012) and the subsequent practice of ambidexterity have been largely discussed (Koryak et al., 2018).

Given the significance of ETI in corporate survival and growth, substantial scholarly attention has been paid to how companies can improve their ETI. Accordingly, various antecedents of ETI have been identified, including government policies (Dolfsma and Seo, 2013), enterprise restructuring (Genin et al., 2021), competition between business giants (Gnyawali and Park, 2011), and management of intellectual property rights (Magelssen, 2020). However, previous studies have considered ETI as a holistic variable and ignored its hierarchical heterogeneity. ETI can be assessed in terms of quantity, quality, and efficiency (Cruz-Cázares et al., 2013; Kong et al., 2020).

This study focuses on quality and efficiency because they are the most relevant factors for research and development (R&D) (Chin et al., 2021; Yuan et al., 2022). To the best of our knowledge, no prior study has discussed ETI quality and efficiency in innovation research. Although few studies have simultaneously examined ETI quality and quantity (Mao and Weathers, 2019; Yu et al., 2018), they have only focused on the output side of innovations without considering the link between input and output, that is, ETI efficiency. Enterprises with high ETI efficiency can achieve superior financial performance (Xie et al., 2020), which, to some extent, can play a role in regional industrial upgrading and development (Haschka and Herwartz, 2020; Wu and Liu, 2021).

The separation of ownership and management in contemporary

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firms enables corporate executives and agencies to govern business operations and discover new investment opportunities through a set of means, such as R&D investments (Scoresby et al., 2021). As a key source of ETIs, R&D activities represent experimental and risky processes, which are usually associated with uncertainties (Asimakopoulos et al., 2020). Therefore, managerial risk-taking propensity becomes a focal issue when business owners plan to motivate executives to effectively engage in ETI activities effectively (Barasa et al., 2019). Cao et al. (2019) and Yigitcanlar et al. (2019) suggestied that the best way to promote ETI is through an effective incentive arrangement. Moreover, according to the behavioral agency theory, managerial incentives can effectively alleviate agency problems and motivate executives to undertake risky tasks (Pepper and Gore, 2015; Wiseman and Gomez-Mejia, 1998). If executives are provided with sufficient incentives, they are often willing to undertake risky tasks (Choi et al., 2021). However, the composition of an appropriate incentive and its associated adequate levels remains unclear in existing literature (Biggerstaff et al., 2019). This study seeks to answer this question.

Managerial compensation has been the focus of incentives (Ntim et al., 2019). Several studies have demonstrated that corporate performance is positively correlated with executive compensation (Conyon et al., 2019; Haque et al., 2020) because it can effectively promote corporate R&D investment (Zhong et al., 2021b). Nevertheless, excessive executive remuneration can lead to agency problems and damage firm performance (Antounian et al., 2021; Dah and Frye, 2017). However, ordinary compensation typically fails to motivate the executives. For instance, Yin et al. (2021) show that restricting executive compensation in state-owned enterprises (SOEs) can increase executive turnover and negatively affect corporate performance. Although risk-averse executives are less likely to be affected by compensation levels (Graffin et al., 2020), they deserve compensation commensurate with their efforts (Lee et al., 2019; Sandberg and Andersson, 2022).

Although the relationship between executive compensation and ETI has received scholarly attention, several gaps remain. First, in most of these studies, emphasis has been placed on evaluating how executive compensation strategies drive R&D investments (Cheng, 2004; Tien and Chen, 2012, among others), overlooking other important and robust measures of ETI, such as ETI quality and efficiency. Second, earlier studies reported contrasting results regarding the impact of executive compensation on innovation activities, including a positive (e.g., Fong, 2010), negative (e.g., Cheng, 2004), or no effect (e.g., Tien and Chen, 2012) between the two variables. We believe that the reason for this dispute is the lack of appropriate incentive levels for executive compensation concerning various dimensions of ETI.

To address these important research gaps, this study captures ETI using quality and efficiency dimensions. It uses a threshold model to identify a reasonable executive excess compensation (EEC) range that is compatible with ETIs. We derive several findings using biopharmaceutical companies in China as the research sample. First, an EEC between 0.0592 and 0.1907 is suitable for improving ETI quality. Second, the sample company executives did not receive an appropriate compensation level that matched their efforts to improve ETI efficiency.

For practical and academic reasons, we chose the Chinese biopharmaceutical industry to study the effects of EEC on ETI. From a practical perspective, the Chinese biopharmaceutical industry significantly contributes to the global market. China is a leading producer of pharmaceutical ingredients and had the second-largest biopharmaceutical market in the world as of 2017 (Abbott, 2017). Despite such success, the quality of innovation in the Chinese biopharmaceutical industry is concerning, which raises doubts about the long-term competitiveness of the industry in the global economy. For instance, a McKinsey report found that although in 2020, researchers in China published the second-highest number of scientific articles in the world, only a small percentage of these articles were published in esteemed scientific outlets such as Cell, Nature, and Science. Additionally, Abbott (2017) reported that patented drugs contribute to less than 20 % of the total drug sales in the Chinese biopharmaceutical industry, indicating companies' inability to develop novel products. Finally, Chen et al., (2019, p.222) termed public research institutes, not companies, as the "vehicle for new drug R&D" in China. While the Chinese government has invested a significant amount of public funds to enhance infrastructure, improve regulations, and sponsor public and private R&D (Chen et al., 2019), such initiatives are only useful when individual companies improve their R&D investments and micro-level innovation processes to take advantage of public R&D investments. Hence, it is critical to pay more attention to various micro-level strategies, such as EEC, which can help individual biopharmaceutical companies in China boost their ETI. Finally, to our knowledge, no prior study has seemingly examined EEC strategies and their impact in the context of biopharmaceutical companies' ETI and through this paper, we bridge this research lacuna.

Our study makes three unique contributions to the technological innovation and governance literature. First, by providing a reasonable EEC range for stimulating ETIs, our research confirms and embodies the effectiveness of the behavioral agency theory. This is because it highlights the role of appropriate managerial compensation in ETIs. Second, our study enhances research on corporate governance mechanisms by alleviating the dilemma faced by enterprises in formulating EEC to promote ETI. Our study also responds to the research calls made by recent studies (e.g., Miroshnychenko and De Massis, 2020) by investigating the impact of different corporate governance mechanisms on R&D investment. Finally, to the best of our knowledge, this is the first time that a threshold model has been applied to EEC research on ETI, making a methodological contribution.

The remainder of this paper is organized as follows. First, we review relevant literature and develop two hypotheses. Next, we present the research design and results. The paper concludes by discussing the results, implications, and future research avenues.

2. Literature review

2.1. Enterprise technology innovation (ETI) and its determinants

While organizational and marketing innovation focus on new organizational structures, management processes, or marketing approaches (Bodlaj et al., 2020), ETI is associated with the development of new products/services and processes or the improvement of existing ones (Nathan and Rosso, 2022). Existing research has used patents, publications, new products/ideas, and R&D investments as proxies to measure innovation (Im and Shon, 2019; Wu et al., 2020).

Scholarly attention to the antecedents of ETI can be broadly classified into two streams: macro- and micro-level. Drawing on the institutional theory (North, 1991), previous studies have considered the impact of a set of government policies on ETI (Dolfsma and Seo, 2013), particularly R&D subsidies (Bronzini and Piselli, 2016), tax incentives (Crespi et al., 2016) and public grants (Vanino et al., 2019). Most of these studies report a positive influence of monetary incentives on firms' ETI. For instance, studies (Borah and Ellwood, 2022; Borah et al., 2023) identify government grants as a critical driver for facilitating multi-helix open innovation collaborations among companies, universities, and community organizations, which strengthens companies' capabilities to address the grand challenges that we are facing today.

While most studies observe that government grants positively impact firms' ETI, criticism also exists. For instance, studies have found that state ownership provides firms with convenient access to government grants (Zhou et al., 2017); which reduces the efficiency with which they use these resources for ETI (Wang et al., 2022). Supporting this reasoning, Kong (2020) suggests that increased government spending leads to a decline in ETI. David et al. (2000) find a complementary and substitute effect between public and private R&D in their study. The complementary effect appears for large firms, as they can benefit from pump priming (i.e., extending a government-funded project by using their investments) and knowledge spillover effects (i.e., transferring the learnings from government-funded projects to new private R&D projects). Additionally, scholars have evaluated the influence of talent development programs (Borah et al., 2019; 2021), intellectual property rights regulations (Kwon and Marco, 2021) and environmental regulations (Jiang et al., 2020) on firms' ETI activities. For instance, the strength of IPR regulations may influence firms' patenting activities, with firms showing more interest in patenting in strong IPR regimes, as stronger regulations allow firms to protect their patents (Borah et al., 2023).

Micro-level antecedents have been discussed at both the organizational and individual employee levels. In these discussions, the role of employee incentives has drawn substantial scholarly interest. Incentives provide "extrinsic motivation" (Borah and Ellwood, 2022) for employees to contribute to innovation productivity. Studies have also discussed the implementation of special incentive schemes for R&D workers. This is because individual innovation performance cannot be evaluated as in other industrial tasks, as innovation tasks are not repetitive, which makes it challenging to set key performance indicators (KPI) based on prior performance (Shapira and Globerson, 1983). Extending this discussion, Manso (2017) argued that incentive schemes vary depending on the nature of innovation: exploitation and exploration. For exploitation, a standard pay-for-performance scheme may still work, as exploitation requires the recycling of proven technologies; thus, tasks are defined and outcomes are often predictable (Manso, 2017).

However, the same cannot be argued for exploration, as it involves the augmentation of new technologies, which comes with uncertainty and sometimes failure. Scholars have attempted to identify KPIs, such as the quantity and quality of patents, which could facilitate the development of incentive schemes for exploration activities. In the context of Japanese firms, Onishi (2013) observed a patent-based incentive scheme that offers bonus payments to employees when they a) apply for a domestic patent, b) register for a domestic patent, c) apply for a foreign patent, and d) register for a foreign patent. Furthermore, firms may use special incentives for employees who develop breakthrough ideas to promote idea generation, the first stage of the innovation process (Toubia, 2006).

However, such individual incentives can be detrimental to firms' innovation productivity, as such a scheme may trigger a competitive environment in a firm, giving rise to tension within the organization and "knowledge hoarding" (Jha and Varkkey, 2018) behavior among employees. Accordingly, studies have argued that group-based incentive schemes should be implemented for ETI (Yanadori and Cui, 2013). Others (e.g., Severinov, 2001) have backed profit-sharing plans, particularly incentive stock options suitable for R&D workers, as they instill a common goal among employees, which is to contribute collectively to improving the ETI productivity and profitability of the firm. Scholarly attempts have also been made to extend this discussion and to examine the impact of executive compensation schemes on firms' innovation productivity. Below, we discuss this avenue of literature, establish a research gap, and develop our hypotheses.

2.2. Excess executive compensation and enterprise technology innovation (ETI): The research gap

Executive compensation is considered a key managerial incentive and refers to the ex-ante sum of "…all incentives and rewards, pecuniary and nonpecuniary, arising from the agency relationship' (Pepper and Gore, 2015, 1053). This is because monetary rewards constitute a common approach to encouraging executives to engage in risky behaviors (Shaikh et al., 2019), which is a key antecedent to ETI activities (Giaccone and Sonia, 2022; Mao and Zhang, 2018).

Two theoretical approaches have been used to study the role of executive compensation in ETI activities: upper echelon theory and behavioral agency theory. Studies that use the former (Hambrick and Mason, 1984), argue that the top management team (TMT) makes the most crucial decisions in a firm and, therefore, claim that "if we want to understand why organizations do the things they do, or why they perform the way they do, we must consider the biases and dispositions (such as human capital, experience, and motivation) of their most powerful actors: their top executives' (Hambrick, 2007, p.334). In comparison, agency theory emphasizes that the interests of the agent and principal should be reconciled by designing an effective monitoring system instead of motivating agents (Wiseman and Gomez-Mejia, 1988). In particular, the behavioral agency perspective primarily focuses on top managers' behaviors, interests, and actions by portraying executives as loss- and risk-averse individuals (Gomez-Mejia et al., 2019), who are also sensitive to future contingencies (Martin et al., 2015) in strategic decision-making, such as R&D investment. To achieve superior firm performance, executives must be sufficiently motivated to perform to the best of their abilities (Devers et al., 2008; Pepper and Gore, 2015), with which the interests of shareholders and executives are well aligned. Both theories assume that executives and agents are boundedly rational and that their decision-making is subject to constraints, including motivation, loss, risk, uncertainty, and time preferences (Desjardine and Shi, 2021; Pepper and Gore, 2015).

Using these theoretical perspectives, a substantial number of studies have investigated the relationship between executive compensation and firm performance (e.g., Brick et al., 2006; Conyon et al., 2019, Ozkan, 2011, among others) and a small proportion have focused on ETI activities as a proxy for performance. However, these studies reported contrasting results regarding the relationship between EEC and ETI. On the one hand, studies have reported that CEO compensation generally bolsters innovation performance. For instance, Fong (2010) found that CEO underpayment is negatively associated with firms' R&D spending and that the relationship is stronger for firms that are manager-controlled (compared to owner-controlled firms) and operate in low-R&D-intensive industries, suggesting the importance of paying CEOs in line with the labor market rate for ETI. On the other hand, Cheng (2004) argues that CEOs of performance-based compensation may prioritize investment in other business functions over R&D, as the impact of R&D on short-term stock prices is often negligible, specifically for long-term radical innovation projects. Tien and Chen (2012) found no effect of CEO compensation on behavioral momentum in R&D (measured by R&D spending) post-leadership change.

To summarize, only limited scholarly attention has been paid to explaining the relationship between executive compensation and firms' ETI (also recognized by Tien and Chen, 2012) compared to studying the role of incentives offered to non-executive R&D personnel. Consequently, there are two research gaps in the literature. First, extant literature does not address the constitution of an appropriate incentive for executives. Second, the influence of executive compensation on R&D spending has been tested; however, how executive compensation may affect other important dimensions of ETI, especially quality and efficiency, remains unclear. We address these research gaps by developing and testing the following hypotheses.

2.3. Hypothesis development

EEC may exacerbate agency problems because it provides executives with additional immunity and job security (Dah and Frye, 2017). Therefore, they are less willing to engage in risking-taking behavior and innovative activities in exchange for higher performance. Xia et al. (2022) posited that this may lead to chief executive officer (CEO) overconfidence, further weakening innovation. Meanwhile, EEC is usually accompanied by a concentration of organizational power and inefficiency of efficiency caused by weak corporate governance (Haque et al., 2020) and deteriorating economic rents (Goergen and Renneboog, 2011). However, when executives feel that they are paid less, they may act for their own benefit at the expense of the company's values (Marinovic and Varas, 2019) or voluntarily resign (Wade et al., 2006). Underpayments are frequently associated with executive financial misconduct (Harris, 2009). Even among family businesses, insufficient compensation offsets the positive impact of family ownership on agency costs (Mazur and Wu, 2016). Additionally, empirical evidence shows that option-based compensation does not drive innovation (Biggerstaff et al., 2019), but cash payouts do (Dittmann et al., 2011). It appears that neither high nor low levels of managerial remuneration stimulate innovation, suggesting that a nonlinear relationship exists between the two. Hence, identifying a reasonable compensation range for different dimensions of technological innovation is crucial. Accordingly, we hypothesize that a nonlinear relationship exists between EEC and ETI. When ETI quality and efficiency change, this relationship is accordingly affected.

Hypothesis 1a. *There is no linear relationship between executive excess compensation and ETI.*

Hypothesis 1b. *Across different technological quality and efficiency levels, the relationship between executive excess compensation and ETI is different.*

3. Methodology

3.1. Sample

Technological innovation in biopharmaceutical companies covers many areas, including physics, chemistry, physiology, and medicine. During the coronavirus disease-2019 (COVID-19) pandemic, there was an urgent demand for technological innovation in such companies. As a sample, we selected China's A-share listed companies from the biopharmaceutical industry (industry code C27) between 2012 and 2020. We used this sample to explore the types of EEC that can promote ETI with different dimensions. Given the significant lag effect between innovation input and output, compared with the other variables, our dependent variables (ETI quality and efficiency) are dealt with by a one-year lag in our research (Yuan et al., 2022).

Observations with missing information were excluded from analysis. All control variables are winsorized at the upper and lower percentiles. The R&D and patent data used in our research sample were derived from the Chinese Research Data Services Platform (CNRDS). Data on accounting and corporate governance were extracted from the China Stock Market and Accounting Research (CSMAR) and Wind Economic databases. These databases have been widely used by researchers (e.g., see Hass et al., 2016).

3.2. Dependent variable

We divided ETI into quality and efficiency. Given that patent data can objectively reflect the progress of innovation (Tian et al., 2020) and that the application year of the patent is better at capturing the actual effective time of innovation activities in a timely manner (Thong, 2018), we use these as raw data for measuring ETI. Although the value of individual patents may serve as a suitable proxy for *ETI quality* (*Ino_qal*), the measurement methods vary (Fisch et al., 2017). The Patent Law of the People's Republic of China divides patents into three types: inventions, utility models, and designs. Invention patents represent the core technical achievements of an enterprise and are considered to be of high ETI quality (Liu et al., 2021; Yu et al., 2018). Existing literature has used the ratio of the number of invention patents to the total number of patents as a surrogate variable for ETI quality (Duan et al., 2021).

This measurement method has two limitations. First, if an enterprise applies for only two invention patents in a certain year, *Ino_qal* of the enterprise in that year is 1 ($2/2 = 1$). However, if another enterprise applies for 15 invention patents, 10 utility model patents, and 5 design patents in the same year, its *Ino_qal* is only 0.5 ($15/30 = 0.5$). Second, only invention patents are counted, and utility model and design patents are excluded, which means that the latter two types of patents have no value. Both of these points are inconsistent with reality. Therefore, we develop a new measurement that assigns different weight coefficients to the three types of patents according to innovation value and then add them together. Specifically, the weights of invention, utility model, and design patents were 0.5, 0.3, and 0.2, respectively.

To gauge *ETI efficiency* (*Ino_eff*), we followed the definition of ETI efficiency (Cruz-Cázares et al., 2013). Accordingly, we considered the number of patents generated per unit of R&D investment a new measurement method. R&D is the only measure of innovation input that has been frequently used over a long period (Machokoto et al., 2021), and patents have been widely used in recent studiesas to measure innovation output (Garcia-Vega and Vicente-Chirivella, 2020). In this study, we combined these two measures to capture the efficiency with which firms convert R&D inputs into final innovation outputs. Therefore, ETI efficiency, following Yuan et al. (2022), is calculated as follows:$Ino\_eff_{i,t+1} = Ln(1 + pat_{i,t+1})/Ln(1 + rd_{i,t})$. Where $pat_{i,t+1}$ is the number of patents filed by company *I* in year t + 1; $rd_{i,t}$ represents the R&D investment of company *i* in year *t*; $Ino\_eff_{i,t+1}$ is technological innovation efficiency of the company *i* in year *t + 1*. Given the time taken to convert R&D investment into patent output, we used a one-year lag. We used one plus log for two reasons. First, in traditional mathematical expressions, the denominator cannot be zero. Second, the gap between values is too large, and taking logarithms can reduce the data bias.

3.3. Independent/Threshold variable

Schulz and Flickinger (2020) calculated the deviation of the total compensation of a firm's CEO in a certain year from the median of the compensation of CEOs from the ten largest firms in the same industry and used it as a surrogate for EEC. However, our research treats this as part of the actual remuneration minus the executives' due remuneration. Based on the literature (Dikolli et al., 2021; Haynes et al., 2017), the following steps were performed before the sample was regressed by year: 1. Delete the initial public offerings in the current year's samples of listed companies, 2. deletion of missing values in the sample and 3. trim the continuous variables by 1 %. The average total salary of the top three executives in logarithmic terms is taken as the manager's actual salary. The due salary is obtained using the regression in Model (1). The residual ε in Model (1) is the excess remuneration of firm *i* in year *t*.

$$\begin{aligned} Manpay_{i,t} = {} & \beta_0 + \beta_1 Size_{i,t} + \beta_2 Lev_{i,t} + \beta_3 ROA_{i,t} + \beta_4 Bod_{i,t} + \beta_5 Mhold_{i,t} \\ & + \beta_6 SOE_{i,t} + \beta_7 Dual_{it} + \sum Year + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where *Size* is the scale of the company, expressed in logarithmic total assets of the enterprise; *Lev* is the company's debt-to-asset ratio, expressed as the ratio of total liabilities to total assets; *ROA* is the return on total assets; *Bod* is the number of board members; *Mhold* is the management holdings, which is the share ratio expressed by dividing the number of shares held by the management by the total number of company shares; *SOE* is a dummy variable that determines whether a firm is a state-owned enterprise; *Dual* is a dummy variable for the combination of chairman and general manager; and *Manpay* is the logarithmic average salary of the top three executives.

3.4. Control variables

To account for alternative factors that may influence ETI, we controlled for certain company characteristics, as suggested in previous studies (Graffin et al., 2020; Schulz and Flickinger, 2020).

We divided these characteristics into two aspects: firm performance and corporate governance. For firm performance, we selected operating income (*Sale*), long debt-to-asset ratio (*Lev*), net profit margin on total assets (*ROA*), and return on investment (*Tobin Q*). This is because good financial performance is the foundation of innovative activities. For corporate governance, we controlled for the shareholding ratio of executives (*Mhold*) and largest shareholders (*Top1*), because effective corporate governance is beneficial for innovation activities.

4. Results

4.1. Descriptive statistics

Given that the threshold model requires strongly balanced panel data for variable matching and purification, we considered 768 valid observations in terms of ETI quality and efficiency, as shown in Table 1.

4.2. Threshold model

First, we considered the standard static panel regression model and split it into fixed- and random-effects models as follows:

$$Ino_{it} = \alpha_1 EEC_{it} + \beta CV_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

where i is the firm; t is the year; *Ino* is ETI, which represents ETI quality and efficiency;*EEC* is executive excess compensation; *CV* is a set of control variables; and μ_i is the intercept term for individual heterogeneity. If μ_i is related to the explanatory variable, the panel data have fixed effects; otherwise, they have random effects. ε_{it} is a perturbation term that varies with time and between individuals.

Based on Equation (2), we further verified whether a nonlinear relationship exists between *Ino* and *EEC*, particularly the threshold effect. Following the threshold effect model proposed by Hansen (1999, 2000), we adopted a sequential method to test the number of thresholds and built the following threshold model for a single threshold:

$$\begin{cases} Ino_{it} = \beta_1 CV_{it} + \alpha_1 EEC + \mu_i + \varepsilon_{it}, if z_{it} \leqslant \gamma \\ Ino_{it} = \beta_2 CV_{it} + \alpha_2 EEC + \mu_i + \varepsilon_{it}, if z_{it} > \gamma \end{cases} \tag{3}$$

In Equation (3), γ is a specific function. In other words, γ is the threshold at which a research sample can be divided into two different intervals. z is a threshold variable that indicates the *EEC* in our study. Given the hysteresis effect of technological innovation, we combined the piecewise functions of Equations (3) and (4) as follows:

$$Ino_{i,t+1} = \beta CV_{i,t} + \alpha_1 EEC_{i,t} I\left(z_{i,t} \leqslant \gamma\right) + \alpha_2 EEC_{i,t} I\left(z_{i,t} > \gamma\right) + \mu_i + \varepsilon_{i,t} \tag{4}$$

$I(.)$ is an indicator function that takes the value of 1 when the conditions in parentheses are satisfied; otherwise, it takes the value of 0. Equation (4) is a panel data model that assumes a single threshold. However, in practice, there may be two thresholds. Therefore, the double-threshold model (5) was constructed based on Equation (4).

$$\begin{aligned} Ino_{i,t+1} = \beta CV_{i,t} + \alpha_1 EEC_{i,t} I\left(z_{i,t} \leqslant \gamma_1\right) + \alpha_2 EEC_{i,t} I(\gamma_1 < z_{i,t} \leqslant \gamma_2) \\ + \alpha_3 EEC_{i,t} I\left(z_{i,t} > \gamma_2\right) + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{5}$$

In Equation (5), when the value of γ_1 is given, an optimal value of γ_2 is obtained by minimizing the sum of squared residuals. Likewise, when γ_2 is fixed, the residual sum of squares is minimized, leading to the optimal search for γ_1. γ represents the specific threshold value estimated in accordance with the data characteristics during the establishment process of the panel data threshold model. A threshold value with the least estimated residual sum of squares of the model was considered to be optimal. Thus, for each given set of γ s, the model was first regressed

Table 1
Variable Descriptive Statistics.

Variables	obs	Mean	Std. dev.	Min	Max
Ino_qal	768	3.476	7.828	0.000	83.7
Ino_eff	768	0.070	0.069	0.000	0.283
EEC	768	0.093	0.577	–1.696	1.569
Sale	768	21.409	1.092	18.103	24.392
Lev	768	0.046	0.070	0.000	0.623
ROA	768	0.073	0.062	–0.118	0.221
TobinQ	768	2.689	1.588	0.929	8.430
Mhold	768	0.051	0.122	0.000	0.795
Top1	768	0.331	0.136	0.083	0.716

to identify the corresponding residual sum of squares, and then the corresponding threshold value was obtained by minimizing the residual sum of squares.

After obtaining the estimated value of the parameter, we performed a significance test for the threshold effect and the estimate. The former was tested using an F-test. The null hypothesis is that there is no threshold effect (i.e., $H_0 : \beta_1 = \beta_2$), and the alternative hypothesis is $H_1 : \beta_1 \neq \beta_2$. The formula for the F-statistic was $F = SSE_0(\gamma) - SSE_1(\widehat{\gamma})/\widehat{\sigma}^2$. Given that the F value is not normally distributed, this study adopted a sampling method to estimate the probability of occurrence of a null hypothesis. Additionally, SSE_0 indicates the residual sum of squares without a threshold effect and SSE_1 indicates the residual sum of squares under the threshold effect. For SSE_1, we used the likelihood ratio (LR) to test the threshold estimate. The null hypothesis is $H_0 : \gamma = \widehat{\gamma}$. The distribution of the LR statistic is nonstandard. When the asymptotic statistic is less than the LR value, the null hypothesis can be rejected, that is, $LR(\gamma) > c(\alpha)$. Among them, the likelihood statistic is $LR(\gamma) = SSE_1(\gamma) - SSE_1(\widehat{\gamma})/\widehat{\sigma}^2$ and the asymptotic statistic is $c(\alpha) = -2\log(1-\sqrt{1-\alpha})$.

4.3. Stationarity test and Hausman test

4.3.1. Stationary test

Given that panel data contain time-series components, we must test their stationarity. To avoid unreliable empirical results, such as spurious regression, LLC (Levin–Lin–Chu), HT (Harris–Tzavalis), and Lagrange multipliers (LM) were used to test the main variables with time-series components. The results of the unit-root tests are presented in Table 2. The results show that each variable rejected the null hypothesis of the unit root at the 1 % significance level, indicating that each variable belongs to a stationary series.

Moreover, the Augmented Dickey-Fuller (ADF) test is frequently used to assess stationarity (Harvey et al., 2013; Francq et al., 2008). The null hypothesis of this test assumes that all panels contain unit roots. Otherwise, at least one panel was considered to be stationary. In an ADF test, if two or more of the four statistical indicators (inverse chi-squared, inverse normal, inverse logit t, and modified inv). Chi-squared for the variables of interest is significant, and the null hypothesis is rejected. Table 3 presents the test results. Stability was guaranteed because all variables had at least three statistical indicators with significant p-values.

Furthermore, given the large number of explanatory variables involved in our nonlinear regression model, we tested for multicollinearity. The results are presented in Table 3. We reported only the tests for multicollinearity related to ETI quality (*Ino_qal*). The Pearson's correlation coefficients and Spearman's rank correlation matrix between the variables are presented in Table 4. Excluding the relatively high correlation coefficient between *TobinQ* and *ROA* (0.498), all other correlation coefficients are less than 0.4, that is, they are relatively weak. Multicollinearity diagnosis was performed using the variance inflation factor (VIF) method. The calculation results show that the mean VIF value is 1.27 (1.27 < 10), which rejects the existence of multicollinearity in the model. As a rule of thumb, the model did not exhibit multiple collinearity when the maximum VIF was less than 10.

4.3.2. Hausman test

To further identify which model (fixed or random effects) is comparatively suitable for this research, we adopted the Hausman test (Torres-Reyna, 2007). Specifically, for a given dependent variable (*Ino_qal* and *Ino_eff*), we performed fixed-effects and random-effects analyses and compared the coefficients of each variable for the different effects. The associated details are listed in Table 5. Following prior practices (Olanrewaju et al., 2019; Torres-Reyna, 2007). We then examined the p-values of the models. If the value was less than 0.05, a fixed effect was preferred. Otherwise, the random effect is ideal. Table 5

Table 2
Unit root test for each variable.

Variables	LLC test		HT test		LM test		Results
	Adjusted t	p-value	z	p-value	Statistic	p-value	
Ino_qal	–5.771	0.000	–9.777	0.000	5.133	0.000	No unit root
Ino_eff	–32.383	0.000	–11.251	0.000	10.626	0.000	No unit root
EEC	–26.376	0.000	–7.308	0.000	15.272	0.000	No unit root
Sale	–17.378	0.000	1.493	0.932	27.101	0.000	No unit root
Lev	–73.694	0.000	–6.668	0.000	14.198	0.000	No unit root
ROA	–19.641	0.000	–10.818	0.000	9.929	0.000	No unit root
TobinQ	–9.690	0.000	–8.612	0.000	3.996	0.000	No unit root
Mhold	–1.6e + 02	0.000	–4.923	0.000	13.819	0.000	No unit root
Top1	–2.2e + 03	0.000	–3.462	0.000	20.733	0.000	No unit root

Table 3
Augmented Dickey-Fuller test for stationary.

Variables	Inverse chi-squared		Inverse normal		Inverse logit t		Modified inv. chi-squared	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Ino_qal	603.706	0.000	0.1841	0.573	–7.443	0.000	21.010	0.000
Ino_eff	895.391	0.000	–2.738	0.003	–14.394	0.000	35.895	0.000
EEC	650.268	0.000	–0.667	0.253	–8.550	0.000	23.386	0.000
Sale	900.220	0.000	–6.1571	0.000	–17.788	0.000	36.141	0.000
Lev	1565.892	0.000	–15.303	0.000	–37.368	0.000	70.111	0.000
ROA	710.054	0.000	–2.424	0.008	–11.150	0.000	26.437	0.000
TobinQ	1268.980	0.000	–13.616	0.000	–30.549	0.000	54.959	0.000
Mhold	735.278	0.000	0.833	0.798	–9.216	0.000	27.724	0.000
Top1	710.672	0.000	–1.807	0.035	–11.004	0.000	26.468	0.000

Table 4
Correlation coefficient test.

	Ino_qal	*EEC*	*Sale*	*Lev*	*ROA*	*TobinQ*	*Mhold*	*Top1*
Ino_qal	1.000	–0.028	0.117***	0.015	0.055	0.048	0.213***	0.052
EEC	–0.013	1.000	0.059	0.089**	0.022	0.032	–0.100***	–0.128***
Sale	0.159***	0.085**	1.000	0.282***	0.212***	–0.246***	–0.204***	0.167***
Lev	0.034	0.082**	0.236***	1.000	–0.357***	–0.315***	–0.206***	0.031
ROA	0.090**	0.015	0.195***	–0.375***	1.000	0.498***	0.114***	0.167***
TobinQ	0.000	0.035	–0.200***	–0.225***	0.419***	1.000	0.072**	–0.023
Mhold	0.097***	–0.128***	–0.162***	–0.109***	0.076**	0.054	1.000	–0.083**
Top1	0.025	–0.074**	0.173***	0.005	0.208***	0.001	0.102***	1.000

Note: Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells report Spearman's rank correlation; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Hausman Test for model selection.

Variables	Innovation quality (*Ino_qal*)				Innovation efficiency (*Ino_eff*)			
	FE	RE	Difference	S.E.	FE	RE	Difference	S.E.
EEC	–0.4278	–0.2513	–0.1765	0.3097	0.0020	0.0016	0.0004	0.0020
Sale	–0.2615	0.4686	–0.7301	0.2446	–0.0150	–0.0090	–0.0060	0.0017
Lev	0.3266	1.7147	–1.3881	1.1123	–0.0058	0.0122	–0.0180	0.0074
ROA	3.6101	5.4677	–1.8576	1.2698	0.0884	0.1006	–0.0122	0.0071
TobinQ	0.4452	0.3867	0.0585	0.0572	0.0027	0.0021	0.0006	0.0003
Mhold	8.7717	9.5632	–0.7915	1.3551	0.0631	0.0707	–0.0076	0.0087
Top1	6.4619	0.4684	5.9935	3.0324	0.0688	0.0397	0.0291	0.0220
chi-squared	17.10				23.32			
P-value	0.0472				0.0055			

Note: FE and RE are the fixed and random effects, respectively. Difference refers to the difference between FE and RE, and S.E. is the standard error.

shows that the largest p-value is 0.0472 (<0.05); thus, fixed effects models constitute a suitable solution to this study.

4.4. *Threshold effect test and estimate*

ETI in any dimension is closely associated with R&D activities. Different EEC incentives cannot directly affect ETI but can indirectly affect ETI by affecting R&D decisions. Following Wang (2015), we considered R&D investment to be an independent variable that varies by regime. Specifically, we calculated R&D investment in millions of RMB. We used the "bootstrap" method proposed by Hansen (2000). Accordingly, we overlapped the simulation likelihood ratio test statistic 300 times and estimated the corresponding bootstrap p-values. In Table 6, considering the ETI quality (*Ino_qal*) as an example, we performed a single threshold test. The obtained F-statistic value was 25.77, and its corresponding bootstrap P-value was 0.08, indicating the significant presence of a single threshold. The double-threshold test finds that its F-statistic value is 33.52, and the corresponding bootstrap P-value is

Table 6
Threshold effect test and estimate for innovation quality and efficiency.

Explained variable	Threshold	F stat	P-value	Threshold value	Lower	Upper
Ino_qal	Single	25.77*	0.080	0.0592	−0.1301	0.0640
	Double	33.52**	0.047	0.1907	0.1878	0.1942
	Triple	22.48	0.177			
Ino_eff	Single	27.40***	0.007	−0.2987	−0.3096	−0.2908
	Double	6.77	0.547			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

0.047, indicating that the double threshold is also significant. This double-threshold effect supports hypothesis 1b. Finally, a three-threshold test was performed, and the bootstrap p-value obtained was 0.177, which was not significant. Therefore, there were only two threshold values. Therefore, we finally find that except for the double thresholds for ETI, quality (*Ino_qal*) and efficiency (*Ino_eff*) have a single threshold that is significant at the 1 % level.

Further analysis shows that when the dependent variable is *Ino_eff*, the threshold value of excess compensation (*EEC*) is −0.2987, and the threshold interval is [−0.3096, −0.2908]. Additionally, when the dependent variable is *Ino_qal*, there are two threshold estimates, 0.0592 and 0.1907, with corresponding threshold intervals of [− 0.1301, 0.0640] and [0.1878, 0.1942], respectively. In contrast to ETI quality, which focuses only on the innovation output side, ETI efficiency combines innovation input and output, and pursues the maximum output for a given input. Therefore, it is considerably difficult for executives to improve efficiency rather than quality, and they deserve more compensation. However, compared with the first threshold value of ETI quality (0.0592), the threshold value of ETI efficiency is −0.2987 (see Table 6), which is significantly lower than the ETI quality. This suggests that executives are not commensurately compensated for, given their efforts to implement ETI efficiency.

4.5. Threshold regression

Using Chinese listed biopharmaceutical companies as the research object, we explored the impact of China's current EEC on ETI quality and efficiency. Table 7 shows the complex nonlinear relationship between the two, verifying Hypothesis 1a. Considering the ETI quality (*Ino_qul*) as an example, combined with Table 6, we obtained two thresholds for the impact of EEC on ETI quality: 0.0592 and 0.1907. Hence, when EEC is lower than 0.0592, R&D investment cannot improve ETI quality. If there is a continuous increase in EEC to 0.1907, R&D investment can strongly promote ETI quality. The coefficient of R&D investment is 0.0144, which is significant at the 1 % level. However, when EEC continues to rise and exceeds 0.1907, R&D investment hinders ETI quality improvement.

Additionally, the impact of EEC on ETI efficiency (*Ino_eff*) has a threshold value of −0.2987. Although R&D investment has a weak negative effect on ETI efficiency (the coefficient of *R&D* is −0.0001) in the presence of excess salary, the coefficient gradually increases and approaches a positive value with a continuous increase in EEC. Among the control variables, *TobinQ*, *Mhold*, and *Top1* promoted ETI to varying degrees. There are two possible reasons for this. First, an increase in corporate market value eases financing constraints, thereby promoting innovation. Second, equity incentives ease agency problems and align the long-term interests of executives and shareholders, consequently emphasizing innovation.

Table 7
Threshold regression analysis.

Variables	*Ino_qal*	*Ino_eff*
Sale	−0.3818 (−0.83)	−0.0126*** (−3.42)
Lev	3.1453 (0.78)	−0.0412 (−1.24)
ROA	3.1214 (0.70)	0.0638* (1.73)
TobinQ	0.4298** (2.43)	0.0028* (1.90)
Mhold	0.0902*** (3.16)	0.0006*** (2.72)
Top1	7.2378* (1.72)	0.0836** (2.41)
R&D_1	−0.0033 (−1.17)	−0.0001*** (−4.44)
R&D_2	0.0144*** (5.48)	−8.51e-06 (−0.94)
R&D_3	−0.0019* (−1.88)	
Cons	3.5655*** (13.07)	0.3058*** (3.88)
R^2	0.0799	0.1071

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; the t-values of the coefficients are in parentheses.

Enterprises are the main drivers of the national economy, and innovation is critical for them to implement sustainable development. How can existing EEC improve ETI quality but have little effect on ETI efficiency? The Chinese government advocates high-quality economic development, and high-quality ETI is considered the foundation for achieving this target. Further analysis in Table 7 shows that China's biopharmaceutical industry pays more attention to ETI quality but ignores ETI efficiency. Although the existing EEC slightly hinders ETI efficiency, this negative effect diminishes as the compensation increases.

4.6. Robustness test and endogenous discussion

4.6.1. Alternative measures of the variables

Generally, a patent cited by a larger number of future inventors has greater value than a patent cited by fewer inventors (Chin et al., 2021). Additionally, patent breadth is a novel way to measure ETI (Akcigit et al., 2022). Thus, we also used three-year cumulative citations of patents as an alternative method to ETI quality (*Ino_qal2*). Given that the currently available patent citation data were updated in 2020, we could only calculate citations up to 2017 and obtain 294 valid observations. Additionally, based on the literature (Shen and Zhang, 2018; Xu et al., 2023), we use invention patents per unit of R&D investment as a surrogate variable to measure innovation efficiency: $Ino\_eff2_{i,t+1} = Ln(1 + inv_{i,t+1})/Ln(1 + rd_{i,t})$. Table 8 presents the results of the study.

After changing the measurement of ETI quality, two thresholds (0.0699 and 0.0750) continue to exist. Both thresholds are significant at the 5 % level, and their overall intervals are [0.0547, 0.0767]. Although the threshold value and interval have changed slightly, this interval is still a part of [−0.1301, 0.1942], compared with Table 6. Moreover, the threshold value and range of ETI efficiency are consistent with those in Table 6.

4.6.2. Instrumental variable test

A valid instrumental variable should satisfy the exogeneity and correlation conditions. We chose the intra-firm pay gap (*Paygap*) as the instrumental variable in this study. Based on existing research (Faleye et al., 2013), we used the ratio of the management team's average salary to the average salary of employees as a proxy variable for the intra-firm pay gap. The intra-firm pay gap is closely related to EEC, but is not directly related to ETI. However, if the instrumental variable contains little information about the explanatory variables, the instrumental variable method estimation using this information is inaccurate. Such instrumental variables are called "weak instruments" (Grilli et al., 2020; Staiger and Stock, 1997). To evaluate whether *Paygap* is a weak instrument, we conduct two-stage least squares (2SLS) regression using instrumental variables (iVs). We tested the significance of the

Table 8
Threshold estimation after changing the variable measurement method.

Explained variable	Threshold	F stat	P-value	Threshold value	Lower	Upper
Ino_qal2	Single	22.41**	0.023	0.0699	0.0547	0.0736
	Double	42.53***	0.003	0.0750	0.0592	0.0767
	Triple	25.16	0.477			
Ino_eff2	Single	20.17**	0.030	–0.2987	–0.3096	–0.2908
	Double	6.77	0.547			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

instrumental variable to obtain the F-statistics in the first stage. Based on existing research (Fassio, 2018), if the F-statistic is greater than 10, there are no weak instruments. For ETI quality and efficiency, the F-statistics corresponding to the instrumental variable (*Paygap*) were 556.563 and 587.097, respectively. Both statistics exceeded 10, indicating that there were no weak instruments.

We adopted the generalized method of moments (GMM) for instrumental variable testing. The corresponding results are presented in Table 9. An improvement in the existing EEC can significantly improve ETI quality, but it has a very limited effect on promoting ETI efficiency. It is worth affirming that the impact of the increase in EEC on innovation efficiency is positive, which is consistent with previous analysis.

4.6.3. Excluding the effects of COVID-19

As an exogenous shock, COVID-19 has significantly affected business and innovation activities. To exclude the influence of COVID-19 on the conclusions of this study, we eliminated 96 observations from 2020 and re-estimated their threshold values. See Table 10.

Table 8 shows that ETI quality and efficiency have two and one thresholds respectively, consistent with Table 6. For ETI quality, one of the two thresholds changed from 0.0592 to 0.0518, while the other remained unchanged. For ETI efficiency, the threshold remained at –0.2987, but its range is slightly reduced from [–0.3096, –0.2908] to [–0.3088, –0.2894]. Overall, after excluding the effects of COVID-19, our conclusion remains robust.

4.7. Heterogeneity analysis

As our study focuses on the biopharmaceutical industry, industry heterogeneity can be ignored. However, regional and ownership heterogeneity warrant further investigation. China is a vast territory, and its development between regions is unbalanced. For instance, the overall economic scale of the eastern regions was significantly better than that of the midwest regions. Moreover, many Chinese listed companies have a governmental background, which is why their operations are quite different from those of non-state-owned enterprises (non-SOEs).

4.7.1. Regional heterogeneity analysis

Table 10 estimates the thresholds for ETI quality and efficiency for the eastern and midwestern regions. We found that both regions have two thresholds in terms of ETI quality, significant at the 5 % level, which is consistent with the results in Table 6. However, the two thresholds in the midwestern area were higher than those in the eastern area. Generally, prosperous regions tend to have higher wages, and the threshold value of the eastern region should theoretically be higher than that of the midwestern regions. However, EEC was relatively high in the present study. This difference between actual and due compensation indicates that executives in the eastern region are not compensated commensurately. This indirectly leads to a negligible impact on the ETI efficiency under the current EEC.

Table 11 shows that there is no threshold effect of EEC on ETI efficiency (*Ino_eff*) in the eastern area because the p-value of a single threshold is not significant; therefore, we only report ETI quality (*Ino_qal*). When the threshold value of EEC is lower than –0.6414, R&D investment can significantly improve ETI quality; currently, the coefficient is 0.0633 at the 1 % significance level (see the first column in Table 12). As EEC continues to rise and cross –0.6414, R&D investment hinders ETI quality improvement. This inhibitory effect can be gradually alleviated if EEC irises beyond –0.3166, and the coefficient of *R&D* increases from –0.0241 to –0.0023. The relationship between *EEC* and *Ino_qal* in the eastern area is N-shaped.

In the midwest area, when the EEC threshold is below 0.1758, R&D investment does not improve the ETI quality. As EEC rises and reaches the interval [0.1758, 0.1907], R&D investment can significantly promote ETI quality, with a coefficient of 0.1048 (see the second column in Table 12). Although there is a threshold value of –0.2992 for EEC and the coefficient of *R&D* is also significant (–0.0002), it is almost close to 0. This finding suggests that executives are not paid in proportion to their efforts when implementing more difficult ETI efficiency. The only certainty is the coefficient also gradually increases that with a continuous increase in EEC.

4.7.2. Ownership heterogeneity analysis

In SOEs, because the p-value of the F-statistic is not significant for ETI quality (*Ino_qal*) and efficiency (*Ino_eff*), there is no threshold for EEC (see Table 13). Existing literature has shown that Chinese SOEs have low operational efficiency and high agency risks (Genin et al., 2021; Vukicevic et al., 2021). For non-SOEs, the number of thresholds for the impact of EEC on *Ino_qal* and *Ino_eff* is consistent with the results in Tables 4 and 6. Nonetheless, the EEC threshold required an improvement in the *Ino_qal* of non-SOEs, which should be higher than that of the entire biopharmaceutical industry and the midwest area.

Table 14 shows that although R&D investment can promote ETI quality, when the EEC is below 0.3093 the positive effect is significantly less than that of the EEC in the interval [0.3093, 0.3398]. This is because the coefficient of *R&D* is 0.0880, which is significantly larger than 0.0050. Once the EEC is greater than 0.3398, R&D investment has a negative effect on ETI quality. Therefore, EEC and ETI quality show a trend of rising first and falling later. In terms of ETI efficiency (*Ino_eff*), there is only one threshold for EEC. When the EEC is lower than –0.2968, R&D investment has a negative effect on *Ino_eff*. However, this negative effect gradually disappears with the continuous increase of EEC.

5. Discussion

Our results show that [0.0529, 0.1907] is the optimal EEC range conducive to stimulating the ETI quality. However, Chinese biopharmaceutical companies have paid little attention to ETI efficiency. Therefore, the existing EEC cannot improve the ETI efficiency. Our heterogeneity analysis suggests that limiting the EEC in the eastern area to below −0.6414 is beneficial for promoting ETI quality. Furthermore,

Table 9
Instrumental variables GMM regression.

Variables	*Ino_qal*	*Ino_eff*
EEC = Paygap	1.7204** (2.17)	0.0126* (1.70)
CV	Yes	Yes
Obs	768	768
R^2	0.0598	0.0151

Note: CV means control variable; Z-values in parentheses.

Table 10
Threshold estimation after excluding the effects of COVID-19.

Explained variable	Threshold	F stat	P-value	Threshold value	Lower	Upper
Ino_qal	Single	25.83*	0.070	0.0581	−0.1316	0.0613
	Double	47.14**	0.033	0.1907	0.1878	0.1942
	Triple	36.34	0.130			
Ino_eff	Single	25.23**	0.037	−0.2987	−0.3088	−0.2894
	Double	10.62	0.237			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11
Threshold effect test and estimate for firms in different regions.

Explained variable	Threshold	F stat	P-value	Threshold value	Lower	Upper
East Area (480 Obs)						
Ino_qal	Single	38.46**	0.0133	−0.6414	−0.6894	−0.6370
	Double	32.32**	0.0267	−0.3166	−0.3299	−0.3008
	Triple	16.68	0.6133			
Ino_eff	Single	8.19	0.3767			
Midwest Area (288 Obs)						
Ino_qal	Single	28.12**	0.0500	0.1758	0.1373	0.1773
	Double	105.33***	0.0067	0.1907	0.1904	0.1950
	Triple	27.44	0.6400			
Ino_eff	Single	14.17*	0.0800	−0.2992	−0.3200	−0.2987
	Double	10.16	0.2300			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12
Regional Heterogeneity Analysis.

	East Area	Midwest Area	
Variables	*Ino_qal*	*Ino_qal*	*Ino_eff*
Sale	0.4537 (0.72)	0.0912 (0.15)	−0.0099* (−1.90)
Lev	1.0530 (0.22)	−0.5840 (−0.10)	0.0214 (0.43)
ROA	2.6206 (0.47)	1.651 (0.28)	0.1509*** (2.95)
TobinQ	0.34118* (1.66)	0.5461** (2.17)	0.0036* (1.65)
Mhold	0.0345 (0.83)	0.0749** (2.19)	0.0009*** (2.87)
Top1	12.8719** (2.30)	3.2782 (0.56)	0.0123 (0.24)
R&D_1	0.0633***(5.05)	−0.0114*(−1.79)	−0.0002***(−3.69)
R&D_2	−0.0241***(−5.24)	0.1048***(8.73)	−0.00001(−0.31)
R&D_3	−0.0023**(−2.11)	−0.0066 (−1.57)	
Cons	−11.7099 (−0.82)	−0.9662 (−0.08)	0.2581** (2.42)
R^2	0.1590	0.4366	0.1988

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-values of the coefficients are in parentheses.

linking the EEC of SOEs with ETI is effective in encouraging them to attach importance to innovation.

5.1. Implications for research

Our study contributes to research on behavioral agencies by designing a reasonable executive compensation range to promote ETI. In our exploration of EEC's impact on ETI, we find strong support for the tenets of behavioral agency theory, as outlined in the literature review. Consistent with Pepper and Gore (2015) and Wiseman and Gomez-Mejia (1998), our results suggest that appropriately calibrated executive compensation is a pivotal motivator for engaging in risky, yet potentially rewarding ETI activities. This finding echoes the theoretical reasoning discussed earlier, highlighting the nuanced balance between risk and reward in executive decision-making. Although existing studies have provided a good foundation for understanding ETI from the perspective of EEC (Biggerstaff et al., 2019; Dittmann et al., 2011), they have yielded conflicting results. For instance, a high EEC induces agency problems (Antounian et al., 2021), whereas a low EEC fails to motivate executives

Table 14
Threshold regression analysis of non-SOEs.

Variables	*Ino_qal*	*Ino_eff*
Sale	−0.5349 (−1.11)	−0.0136*** (−3.42)
Lev	−2.2371 (−0.46)	−0.0750* (−1.87)
ROA	3.2372 (0.64)	0.3268 (0.79)
TobinQ	0.3991** (2.11)	0.0029* (1.88)
Mhold	0.0861*** (2.93)	0.0006*** (2.62)
Top1	6.5004 (1.45)	0.1001*** (2.69)
R&D_1	0.0050*** (2.62)	−0.0001*** (−4.30)
R&D_2	0.0880*** (6.64)	−9.82e-06 (−1.05)
R&D_3	−0.0024** (−2.13)	
Cons	10.4397*** (1.03)	0.3200*** (3.83)
R^2	0.1450	0.1366

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13
Threshold effect test and estimate for firms with different ownership.

Explained variable	Threshold	F stat	p-value	Threshold value	Lower	Upper
SOEs (192 Obs)						
Ino_qal	Single	13.13	0.1767			
Ino_eff	Single	10.01	0.2800			
non-SOEs (576 Obs)						
Ino_qal	Single	24.58*	0.0567	0.3093	−0.8129	0.3122
	Double	41.75**	0.0200	0.3398	0.2640	0.3444
	Triple	25.03	0.3133			
Ino_eff	Single	22.83***	0.0100	−0.2968	−0.3104	−0.2894
	Double	8.82	0.2867			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

to engage in risky innovation projects. Similarly, Fong (2010), Cheng (2004), and Tien and Chen (2012) find positive, negative, and no effects, respectively, of executive compensation on innovation activities.

This dispute arises because the existing research lacks a reasonable EEC range. In this study, we clarified this debate by identifying the impact boundary of the EEC on ETI. Our identification of an optimal EEC range for enhancing ETI quality is particularly noteworthy. This range, specific to the Chinese biopharmaceutical context, provides empirical support for the theoretical propositions of Biggerstaff et al. (2019) regarding the importance of tailored compensation strategies. While prior studies, such as Conyon et al. (2019), note a positive correlation between executive compensation and corporate performance, our study adds a new dimension by pinpointing an effective compensation range for fostering innovation quality.

This study also contributes to the literature on innovation by measuring ETI in terms of quality and efficiency. Scholars have either considered ETI as an overall variable or have divided it into quantity and quality (Mao and Weathers, 2019). Both streams have focused only on innovation output, and have consequently neglected the investigation of innovation input and output, that is, innovation efficiency. Cruz-Cázares et al., (2013, p.1239) argue that the "undifferentiated use of innovation inputs and outputs to measure firm innovativeness is not without problems, and that, from a productive perspective, they should be simultaneously analyzed (i.e., innovation efficiency)". Although studies by Xie et al. (2020) and Wu and Liu (2021) emphasize the link between innovation efficiency and financial performance, they do not examine the role of compensation in this dynamic. Our study bridges this gap, suggesting a more complex relationship than previously acknowledged, where not just the presence of compensation but its adequacy plays a crucial role. The finding that current compensation levels are insufficient for enhancing ETI efficiency adds a new layer to the ongoing discourse in the literature.

Moreover, in the literature on the impact of executive compensation on ETI, R&D spending has been used as the main proxy for ETI (e.g., see Cheng, 2004; Tien and Chen, 2012). To our knowledge, this is one of the first studies to explain the effects of executive compensation on innovation quality and efficiency. Further, we contribute to corporate governance literature by discussing how EEC can be designed to effectively incentivize executives to perform to the best of their abilities. This effort aligns well with the recent calls for research by Miroshnychenko and De Massis (2020), particularly in examining how governance mechanisms, such as EEC, influence R&D investments. Although the existing corporate governance literature proposes that incentives and supervisory mechanisms can simultaneously help reduce agency problems (Zhong et al., 2021a), the former is more effective (Manso, 2017) for biopharmaceutical firms facing more ETI challenges. Moreover, many empirical studies have failed to prove the effectiveness of monitoring and controlling agent behavior in alleviating agency problems (Dalton et al., 2007). Based on behavioral agency theory, we provide different EEC for different ETI dimensions, which may alleviate agency problems and strengthen corporate governance.

Further, our research on the relationship between EEC and ETI lends support to the consideration of diverse theoretical frameworks, such as tournament theory. This theory posits that the differential in pay among executives fosters a competitive environment, which could potentially spur innovation as executives vie for the top rewards (Connelly et al., 2014). This theoretical lens suggests that excess compensation at the upper echelons may not merely be a reflection of agency problems, but could also be a deliberate strategy to induce higher levels of performance and risk-taking necessary for significant ETI efforts. Through the prism of tournament theory, we may gain a more nuanced understanding of how compensation structures can be strategically designed to enhance competitive advantage through innovation. Equally important, while our study focuses on incremental innovation, the structuring of executive compensation, as theorized by tournament theory, may also incentivize radical and management innovation. These forms of innovation require significant risk-taking and departure from conventional practices, suggesting that competitive executive rewards could drive breakthrough technologies and novel management strategies.

Finally, we make context-specific contributions to the literature. First, in the earlier literature, despite the significance, the executive compensation strategies and their impact on ETI have hardly been studied in the context of the biopharmaceutical industry. Second, the same literature also focuses on evaluating executive compensation strategies in developed Western economies, offering little insight into the design and impact of such strategies in emerging economies. By selecting the Chinese biopharmaceutical industry for this study, we addressed both the research lacunae.

5.2. Practical implications

Our findings offer actionable insights for corporate boards, especially in the Chinese biopharmaceutical industry, to rethink and recalibrate their executive compensation strategies. First, our research provides firms with more options for ETI activities such as ETI quality and efficiency. Although both innovations are significant for firm development, ETI efficiency is more important and difficult to improve (Xie et al., 2020) because it requires a higher EEC, external drivers outside the organization, excellent scientists, and advanced production equipment. Currently, the compensation design of executives in China's biopharmaceutical industry is ineffective in promoting ETI efficiency, which is why the ETI efficiency in this industry is generally low. This is because most companies focus only on improving ETI quality and ignore ETI efficiency. Therefore, enterprises can first focus on improving ETI quality and then gradually turn to efficiency after achieving high-quality ETI.

Second, our findings can help companies optimize executive compensation to promote ETI. For the Chinese biopharmaceutical industry, controlling the EEC between 0.0592 and 0.1907 is most conducive to improving the ETI quality. Controlling the EEC between 0.3093 and 0.3398 for non-SOEs greatly improves ETI quality. Once the EEC exceeds the threshold of 0.3398, it hinders the improvement of ETI quality. In terms of ETI efficiency, an increase in existing EEC can gradually alleviate the negative impact of R&D investment on ETI efficiency. While increased executive compensation may encourage more ETI, it is crucial to consider the possible unintended consequences. High compensation might lead to widening pay disparities, potentially affecting employee morale and fostering a culture that focuses excessively on short-term gains. Additionally, this approach may inadvertently prioritize innovation that aligns with executive interests over what is most strategically beneficial for the company, leading to misaligned organizational goals.

Third, our study provides evidence that the COVID-19 pandemic did not affect the optimal EEC range. Thus, the post-pandemic adjustment of compensation plans is not required. Finally, our results can help local governments to govern SOE executives. Given the political particularity of SOE executives, EEC cannot sufficiently influence ETI. Therefore, it is necessary to improve the SOE salary-supervision system. In SOEs, executives generally do not pay sufficient attention to the ETI. Therefore, the current EEC has no impact on ETI quality or efficiency. We propose linking EEC with ETI in order to change the direction of non-SOEs.

6. Conclusion

We discuss the impact of EEC on the quality and efficiency of ETIs. Based on empirical data on Chinese biopharmaceutical listed firms, a reasonable EEC range has been found to promote ETI quality. It was also found that the existing EEC was insufficient to improve ETI efficiency. After changing the measures of the key variables and using the instrumental variable test, the conclusions of the study were proven robust. Moreover, we found that the relationship between EEC and ETI quality in the eastern region was N-shaped, whereas this relationship was inverted U-shaped for non-SOEs. Additionally, both heterogeneity analyses showed that EEC has only one threshold for ETI efficiency, because an increase in compensation leads to a positive development in ETI efficiency.

Regarding limitations, our study uses only Chinese-listed companies in the biopharmaceutical industry as the research subject. Therefore, whether our conclusions,can be applied to other industries requires further investigation. Furthermore, the international mainstream uses the DEA model to measure efficiency. However, the DEA model has many restrictions (e.g., input and output cannot be zero or negative, and must include strongly balanced panel data), which may reduce the sample size. Finally, because executive compensation is affected by many factors such as the local economy, corporate performance, and executive capabilities, it is challenging to fully capture precise excess compensation.

Future research could explore how these compensation ranges apply in different cultural and industrial contexts. Cross-industry and cross-national analyses could provide a broader understanding of the dynamics between executive compensation and technological innovation as well as help identify the role of institutional differences and public politics. Given the complexity of the relationship between executive compensation and innovation outcomes, longitudinal studies can provide additional insights into the dynamic changes in this association. Future research could track the long-term effects of EEC on ETI by examining how these relationships evolve over time under various economic conditions. Specifically, innovations aimed at addressing grand challenges such as climate change and poverty demand considerable time and resources. The literature and society would benefit significantly if researchers could identify an optimal EEC range that could motivate executives and firms to participate in more societal and sustainable innovations, thereby addressing these grand challenges.

Furthermore, given the novel use of the threshold model in this study, subsequent research could apply similar methodologies across various sectors to validate or refine our findings. Finally, future studies should identify and examine potential mediating and moderating variables that influence the relationship between EEC and ETI. Variables such as organizational culture, leadership styles, and market dynamics could further enrich our understanding of how and when EEC most effectively stimulate ETI.

CRediT authorship contribution statement

Yong Xu: Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Junzhe Ji:** Writing – original draft, Formal analysis, Conceptualization. **Nicolas Li:** Writing – review & editing, Writing – original draft, Investigation. **Dhruba Borah:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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