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Performance Shortfall, Top Management Team Faultlines, and R&D Investment: Evidence from China

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Abstract

With the increasing uncertainty of the world economic situation, enterprises are facing the pressure of downward performance, and R&D has been an important strategic choice to solve the performance fall problem of high-tech enterprises. The article tries to explore the changes in the R&D investment intensity of enterprises under different performance lag levels and investigate the influence of the combination of characteristics of top management team(TMT) members on the strategic decision-making process. It is found that the relationship between the degree of performance disparity and R&D investment intensity is inverted U-shaped; the strength of the fracture faultline of the top management team negatively regulates the relationship between the degree of performance disparity and R&D investment and makes the inverted U-shaped curve flat. A further study of specific characteristic fracture bands revealed that team fracture bands based on tenure characteristics had a significant negative moderating effect, while professional and functional background fracture bands had a significant positive moderating effect. This study not only theoretically expands the understanding of the performance shortall and TMT disconnection on the deep-seated motivation of enterprise R&D investment, but also provides practical references for solving the problem of performance gap, optimizing the allocation of TMT human resources, and rationally promoting enterprise R&D investment to achieve transformation.

Keywords: performance lag, fracture faultline theory, R&D investment, top management team characteristics, governance efficiency

1. Introduction

The complexity and unpredictability of the business operating environment have brought uncertainty and volatility to the performance of companies, especially due to the impact of the New Crown epidemic, which has severely hampered global economic development and made it difficult for Chinese companies to be left alone. Although the effective measures to combat the epidemic in China helped most of the enterprises out of the winter of 2020 and provided a strong guarantee for their recovery in the post-epidemic era, along with the economic downward pressure and the rise of trade protectionism, the external operating environment faced by Chinese enterprises is severe, and a significant proportion of them have not achieved the expected results and urgently need to take change measures to change their plight. Corporate behavior theory suggests that when the actual performance of enterprises is lower than the desired performance, enterprises are in a state of Performance Shortfall (underperformance) when they tend to find ways out of the dilemma through more aggressive strategic change behavior (Greve, 2003). Among the many possible corporate behaviors, R&D and innovation activities are important tools to "break out" of a difficult situation because they can help firms increase output, improve services, or even open up new markets (Dong et al., 2021). The study has found that as a company's performance declines, it is more likely to be able to improve its service. It has been found that as the gap in firm performance increases, firms will increase their R&D investment intensity (Zhong et al., 2022). Firms with insufficient performance may increase overseas R&D investment, especially imitating the innovation strategies of industry leaders, in order to achieve competitiveness (Chen et al., 2023). The executive team will choose high-risk innovation investments through resource allocation in the case of a large performance gap, in an attempt to change the long-term performance of the company (He et al., 2021). However, some scholars believe that the lower the corporate performance, the more cautious the corporate executives' decisions will be, and the more conservative the strategies will be (Kotiloglu et al., 2019). Finally, some scholars believe that the relationship between performance gap and R&D investment is uncertain, depending on whether the enterprise whether they have abundant resources. When enterprises have abundant resources, they are more likely to increase R&D investment in the case of performance gaps, while when resources are limited, they tend to choose conservative strategies (Kuusela et al., 2017; Lv et al., 2019).

The reason for the inconsistent findings is that they do not take into account the fact that as the Performance Shortfall increases, the top management team may change its risk appetite due to the change in its focus on business conditions: when the Performance Shortfall is small, the top management team has a high-risk tolerance and tends to improve its performance through high-yield R&D activities, while when the performance deteriorates or even threatens the survival of the company, it tends to reduce its risky R&D activities to avoid further deterioration. When the performance deteriorates or even threatens the survival of the company, they will reduce the risky R&D investment to avoid further deterioration of the company's condition. Therefore, there should be a non-linear relationship between the degree of performance disparity and the intensity of R&D investment.

In addition, the top management team, as important decision-makers, has a significant impact on various strategic behaviors of the firm. When a firm faces a performance lag, the effectiveness of the top management team's decision-making affects the speed and likelihood of getting out of the situation. Given the team attributes of decision makers, diversity of team characteristics is often the focus of relevant studies. However, existing research has focused only on the proportion of single characteristics such as gender, age, and tenure among team members and has not considered the possibility that the alignment of multiple characteristics in a team may affect the role of a single characteristic (Thatcher et al., 2012). Fracture faultline theory, on the other hand, is a good remedy for this deficiency. A team fracture faultline is a line in the hypothesis of dividing a team into multiple subgroups based on a particular feature, and the overlap of multiple feature fracture faultlines in the way they divide subgroups enhances the strength of the fracture faultline, making it easier for teams to split into substantial subgroups based on this fracture faultline (Lau & Murnighan, 1998). Team fracture faultlines are a multidimensional perspective of feature diversity, where the difference brought by one feature may be weakened by the similarity of another feature or enhanced by the difference of another feature, which in turn affects team members' attitudes and behavioral styles toward each other. Many literatures have proved that the impact of the executive team fault line on different industries is different. Simsek et al. (2005) showed that the division and conflict caused by the fault line in the high-tech industry often weaken the strategic consistency and innovation ability of the enterprise. Beckman et al. (2008) showed that in the technology-based industry, the fault line of the executive team has a significant impact on the strategic decision-making of the enterprise from its inception to IPO. Boone et al. (2004) studied the impact of the fault line of the executive team on strategic decision-making in the traditional media industry, and found that the impact is more conservative than in the rapidly changing industry. In addition, the negative impact of the executive team fault line on innovation strategies is less significant in the manufacturing industry, and it enhances the transformation of the company's related products into services. The executive team fault line can make SMEs more prone to disagreements about innovation investment and strategic adjustments (Lv et al.,2024). Therefore, this study explores what intensity of R&D investment activities firms choose when facing different levels of performance disparity from a performance feedback model, combined with a fracture faultline theory perspective, to reveal the mechanism of the role of top management team characteristics combination in the relationship between performance disparity and the intensity of firms' R&D investment.

2. Theoretical Basis and Research Hypothesis

2.1 Performance Lag and R&D Investment

According to the theory of corporate behavior, to identify the operating status of a firm, a finite rational executive will set a performance expectation level for the firm based on the firm's historical performance or peer performance, and the achievement of this performance expectation will be the criterion for the executive to judge the success of the firm's operation in the current period (Desai, 2016; Greve, 1998). Actual performance above the expected level is often judged as a "success" of the company, while actual performance below the expected level means that there are potential problems in the company, which then triggers a "problem search" mechanism to reduce the Performance Shortfall, and a series of strategic changes or organizational adjustments will be made to the company. changes or organizational adjustments will occur (Kuusela et al., 2017). Research has shown that when faced with a Performance Shortfall, a company's "problem search" mechanism is triggered to narrow the Performance Shortfall. Studies have shown that the possible responses of firms facing a Performance Shortfall include: scaling up, divesting, and investing in R&D. (Shinkle, 2012; Nakauchi & Wiersema, 2015).

Among the many corporate feedback behaviors, companies' R&D investment strategies are highly valued (Lucas et al., 2018). R&D investment is more often used as a way to find innovative products, services, and processes to increase product prices or reduce production costs, in the context of the "Performance Shortfall - problem search - strategic change" mechanism of corporate behavior theory. In the perspective of the "Performance Shortfall - problem search - strategic change" mechanism of corporate behavior theory, the R&D investment is not so much an act of strategic change after a potential problem has been identified, but rather a mechanism of problem search itself, i.e., executives regulate the R&D investment as a means of problem search and then develop strategies to narrow the Performance Shortfall. Therefore, rather than focusing directly on the ultimate strategic change behavior, focusing on the state of R&D investment when a company is facing a Performance Shortfall can help us better understand the actual attitude and strategic tendency of the company toward the current state.

However, the empirical results of the relationship between performance lag and R&D investment do not fully fit the expectations of theories of firm behavior. While some scholars have confirmed that firms facing performance lags increase their R&D investment (Huang et al., 2021). However, some scholars have found that firms in a state of poor performance solve the problem by cutting operating costs rather than increasing R&D investment. (Vidal & Mitchell, 2015) However, some scholars have also found that firms in a performance lag solve the problem by cutting operating costs rather than increasing R&D investment. The risk preferences of policymakers may be one of the best explanatory perspectives for this contradictory result.

Prospect theory suggests that when faced with a fallout state, firms are more willing to take risks and adopt risk-taking behavior to avoid losses (Panagiotou, 2007). Therefore, executives are more likely to adopt high-risk strategies such as increasing R&D investments in the face of poor firm performance (Rudy & Johnson, 2016). However, Dan et al. (1980) experimental study of corporate executives found that decision-makers have a risk preference when faced with a lesser degree of loss and tend to avoid risk only when losses increase or even when there are serious situations that could lead to corporate bankruptcy. Based on this, subsequent research suggests that in addition to the desired level reference point for success, there is also a "survival reference point" for survival. When a firm's actual performance is lower than the desired level reference point but higher than the survival reference point, the firm will try to narrow the gap or reverse it through risk-taking behaviors such as increasing R&D investment. loss status (Joseph et al., 2016). However, when the loss level is close to or even lower than the survival reference point, companies tend to make conservative decisions to ensure their survival. However, when the loss level is close to or even below the survival reference point, firms tend to make conservative decisions to ensure survival and reduce risky behaviors such as strategic changes (Audia & Greve, 2006). This idea is also in line with the expectation of threat rigidity theory, which suggests that executives tend to narrow their search for problems when faced with threats and dilemmas and reduce or even refuse to adjust or change in order to ensure their survival, due to the enormous stress and anxiety they face (Staw et al., 2006). Therefore, even though R&D can be one of the ways to find a way out of the dilemma under the increasing degree of performance fallout, continuing to increase R&D investment may cause the firm to deplete important resources due to its high cost and risk, which may exacerbate the level of distress or even threaten the firm's survival. In summary, the following hypotheses are proposed.

H1: The intensity of firms' R&D investment will rise and then fall in an inverted U-shape as the degree of performance lag increases.

2.2 Moderating Role of TMT Faultline

Executives, as important decision-makers, have a significant impact on the development and implementation of corporate strategies (Blagoeva et al., 2019). In addition, the prospect theory focuses on risk appetite. In conjunction with risk appetite, which is the focus of prospect theory, personal characteristics which represent the cognitive structure and values of executives is another important factor influencing their strategic choices. Research on executive characteristics has generally focused on team heterogeneity, i.e., exploring how the distribution of a single dimension (e.g., gender or educational background) affects the team's decision-making process and outcomes (Ndofor et al., 2015).

However, the traditional perspective of team heterogeneity research is slightly limited, focusing on a single characteristic without taking into account the changes that the interaction of multiple differentiating characteristics may bring to team dynamics. Fracture faultline theory is a good remedy to this deficiency by placing more emphasis on the variability of team members across multiple dimensions, suggesting that the magnitude of influence of a characteristic dimension on team behavior may depend on how other characteristic dimensions are arranged among team members (Lau & Murnighan, 1998). The more similar certain team members are on multiple characteristics, the more likely they are to "stand in line" based on those characteristics, which will serve as the basis for self-identification and social categorization of members, eventually leading to the fragmentation of subgroups within the team. Team fracture faultlines are virtual lines that divide teams into subgroups based on certain characteristics, and the stronger the consistency of characteristics among subgroup members and the weaker the consistency of characteristics among subgroup members, the stronger the team fracture faultline will be (Richard et al., 2019; Shaw, 2004).

Based on social identity theory and self-categorization theory (Turner & Tajfel, 1986), team members tend to be close to members who share their characteristics and alienate members who are less similar to them. When this affective tendency forms substantial subgroups in the team, members will favor members within the subgroup and have a bias against members outside the subgroup, and this differentiation will make the interaction between different subgroups decrease and the communication process is hindered (Georgakakis et al., 2017) This is detrimental to the flow of information and the formation of a good decision-making environment, and prolonged division and contention may even lead to a decrease in members' sense of security or even their identification with the team as a whole (Chung et al., 2015). Some studies have also found that when top management teams have strong fracture faultlines, the likelihood of inter-executive outbursts and the likelihood of conflict between executives increase significantly when the top management team has strong fracture faultlines (Rupert et al., 2016). The potential for conflict between executives increases significantly when the top management team has strong fracture faultlines (Rupert et al., 2016). Therefore, stronger fracture faultlines lead to higher levels of conflict in top management teams, bias among subgroups makes the flow of information blocked, top management team members have difficulty agreeing on a resolution, and a decrease in decision-making efficiency causes the relationship between performance fallout and corporate R&D investment to be negatively moderated. Therefore, the hypothesis is proposed.

H2: Fracture bands of top management teams play a negative moderating role between the degree of performance disparity and R&D investment, i.e., the stronger the fracture band, the lower the firm's R&D investment at the same level of performance disparity.

3. Study Design

3.1 Sample and Data Collection

In this paper, information technology companies listed in A-shares from 2007 to 2018 are used as the research subjects. The information technology industry mainly includes two sub-industries with code I (information technology industry) and C39 (computer communication and electronic equipment manufacturing) in the 2012 industry classification of the China Securities Regulatory Commission.

The core data in this paper mainly come from CSMAR database and RESSET database; in addition, information is supplemented and verified through other means, such as company annual reports, Sina Finance Network, Juchao Information Network, and Flush Finance. Like the data collection methods of previous related studies, this paper excludes ST, PT, and companies with serious data deficiencies, and finally obtains 1541 unbalanced panel data of 328 listed companies.

3.2 Variable Measurement

(1) Explanatory variable: enterprise R&D intensity. In this paper, we measure the intensity of firms' innovation investment in terms of their R&D expenditure/sales revenue. Another commonly used measure, i.e., R&D expenditure/total assets will be presented later as a robust type of test for the findings of this study.

(2) Explanatory variable: degree of performance lag. In order to measure the degree of performance lag, it is first necessary to determine how performance and performance expectations are measured. The vast majority of previous studies on the theory of corporate behavior have used return on total assets (*ROA*) as a measure of corporate performance proxy variable (Shimizu, 2007). As a commonly available and easily calculated indicator in all corporate financial reports, its accessibility and representativeness of corporate profitability make it a financial indicator of greater interest to corporate stakeholders, and corporate executives are more likely to adjust corporate strategy according to stakeholder concerns. Therefore, this paper chooses to use return on total assets (*ROA*) as an indicator of corporate performance. There are generally historical comparison methods and social comparison methods for the measurement of expectation levels, but since there are no definitive conclusions on the reference points for social comparisons, the current relevant studies differ significantly in the selection of reference firms, resulting in the poor comparability of this literature (Lian et al., 2019). Therefore, in this paper, we choose the historical comparison method, which is more consistent in its calculation, to measure the expectation level of firms. The historical-type performance expectation algorithm is $HA_{i,t} = \square P_{i,t-1} + (1-\square)A_{i,t-1}$, where $HA_{i,t}$ *denotes the expected performance of firm i* in period t, $P_{i,t-1}$ denotes the performance of firm i in

period *t-1*, and $A_{i,t-1}$ denotes the expected performance of firm i in period *t-1*. $HA_{i,0}$ is defined by the actual performance in the first year of the data. Where α is a weight parameter between [0,1], which indicates the weight of historical expected performance between the actual performance in the previous period and the expected performance in the previous period. In this paper, we take the value of α as 0.6 by referring to the practice of related scholars (Wen Qiaotian & Guo Rong, 2017). After that, the actual performance of the firm and the historical expected performance are subtracted, and if the result is less than 0, the performance lag state. In this paper, we focus on the behavior of firms in the performance lag state and refer to related studies to construct a truncated continuum variable to measure the expectation lag, i.e., the degree of expectation lag is taken as an absolute value and the value above the expected level, i.e., the performance surplus, is taken as 0.

(3) Moderating variable: TMT faultlines intensity. In this paper, the measures of Thatcher (2003) and Van Peteghem et al. (2018) were selected to measure team fracture faultline strength. First, hierarchical clustering is used to determine the optimal number of groupings of executive level members in each company based on their gender, age, education, tenure, professional, and functional background characteristics; second, K-means clustering is used to iterate the executive level teams into specified groups based on the optimal number of groupings; finally, Thatcher's (2003) formula is used to measure each top management team's fracture faultline strength, which is calculated as follows.

$$fls_g = \frac{\sum_{f=1}^{p}\sum_{k=1}^{q} v_k^g(\bar{x}_{kf}-\bar{x}_f)^2}{\sum_{f=1}^{p}\sum_{k=1}^{q}\sum_{i=1}^{v_k^g}(x_{ifk}-\bar{x}_f)^2} \quad g=1,2,...s$$

where $\bar{x}_{kf}$ denotes the mean of the members of subgroup *k on feature f*, and $\bar{x}_f$ denotes the mean of all subpopulation members on feature *f*, and x_{ifk} denotes the value of feature *f* for member *i* of subgroup *k, and* v_k^g denotes the number of members in the *kth subgroup* under the gth grouping method. The range of fracture faultline intensity values calculated by this formula is (0,1). The higher the strength of the final calculated fracture faultline, the higher the likelihood of team members forming substantial subgroups. In this paper, age, gender, education level, profession, functional background and, length of tenure of top management team members are selected as indicators for the calculation of fracture faultline intensity. The specific classification criteria of the relevant characteristics are as follows: ① gender is divided into male and female; ② age classification refers to the research of related scholars at home and abroad, and the year of birth is divided into four groups: 1928-1945; 1946-1960; 1961-1979; 1980-1995; ③ education level is classified according to secondary school and below, college, bachelor, master, and doctor; ④ tenure are classified as less than three years, more than three years to six years, and more than six years; ⑤ profession is classified as business, humanities, law, information technology, and others according to the major category of the manager's highest degree studied; ⑥functional background is classified as production, R&D, finance, management, marketing, law, personnel, and others.

(4) Control variables: With reference to relevant studies, this paper selects firm bankruptcy risk, unabsorbed redundancy, absorbed redundancy, potential redundancy, firm age, firm size, firm nature, firm growth opportunity, industry competition, industry R&D intensity, and industry outlook as control variables for the empirical study. The reasons are as follows: ① Redundant Resources: The availability of unabsorbed, absorbed, or potential redundancies determines whether a firm can sustain R&D investment. Sufficient redundancy may allow continued or increased R&D investment despite performance gaps, while insufficient resources may lead to cuts. ② Bankruptcy Risk: Higher bankruptcy risk typically leads firms to adopt conservative strategies, often reducing R&D spending to manage short-term financial pressures, thus weakening the influence of performance gaps on R&D. ③ Firm Size, Age, and Nature: Larger, more established, or privately owned firms generally have greater resource availability and risk tolerance, enabling continued R&D investment during performance declines. In contrast, smaller, younger, or state-owned firms may take a conservative approach, reducing R&D investment. ④ Company Prospects: Firms with a positive outlook may continue R&D investment despite performance gaps, while a pessimistic outlook could prompt reduced R&D spending to avoid further risk. ⑤ Industry Competition: In highly competitive industries, firms often increase R&D investment to remain competitive even during performance gaps, whereas in less competitive industries, firms may reduce or maintain R&D levels. ⑥ Industry R&D Intensity: High R&D-intensive industries pressure firms to sustain R&D investment during downturns to stay relevant, while low R&D-intensity industries may see a stronger negative correlation between performance declines and R&D spending. ⑦ Industry Outlook: Optimistic industry prospects encourage firms to boost R&D investment during performance declines, while uncertainty tends to foster a more conservative response, with firms prioritizing short-term survival.

Table 1. Model settings

Variable Name	Variable Symbols	Variable measurement
Corporate R&D intensity	$RD_{i,t}$	R&D expenditure/sales revenue
Degree of performance lag	$shortfall_{i,t-1}$	The absolute value of the difference between actual and expected performance in the performance lag state
TMT Faultlines Strength	$fls_{i,t-1}$	Referring to Thatcher (2003), the probability of forming subgroups of the top management team is measured with a value between 0 and 1
Business bankruptcy risk	$bankruptcy_{i,t-1}$	Measured by Z-index
Unabsorbed redundancy	$unslack_{i,t-1}$	Measured by quick ratio, quick assets/current liabilities
Absorbed redundancy	$abslack_{i,t-1}$	Measured by fee-to-income ratio
Potential Redundancy	$poslack_{i,t-1}$	Measured by equity to debt ratio
Business Age	$firm\ age_{i,t-1}$	The number of years of business establishment as of year t
Enterprise size	$firm\ sizek_{i,t-1}$	Natural logarithm of total corporate assets
Nature of business	$firm\ nature_{i,t-1}$	State-owned nature take 1, other take 0
Business prospects	$firm\ opor_{i,t-1}$	Measured as the average value of the rate of change in sales revenue over the past three years
Industry Competition	$indus\ oppo_{i,t-1}$	Measurement of the number of competitors in the same industry
Industry R&D intensity	$indus\ RD_{i,t-1}$	Measured by the average value of R&D intensity in the same industry
Industry Outlook	$indus\ opor_{i,t-1}$	Measured by the average value of industry sales change rate over the past three years

3.3 Model Setting

To test the relationship between the degree of performance fallout and the R&D intensity of the firm, as well as the moderating effect of top management team disruption, the following model is developed.

$$RD_{i,t} = \beta_0 + \beta_1 shotfall_{i,t-1} + \beta_2 shotfall^2{}_{i,t-1} + \sum Control + \varepsilon_{i,t} (1)$$

$$RD_{i,t} = \beta_0 + \beta_1 shotfall_{i,t-1} + \beta_2 shotfall^2{}_{i,t-1} + \beta fls_{i,t-1} + \theta_1 shotfall_{i,t-1} \times fls_{i,t-1} + \theta_2 shortfall^2 all_{i,t-1} \times fls_{i,t-1} + \sum Control + \varepsilon_{i,t} (2)$$

Among them, the dependent variable of both model (1) and model (2) is R&D intensity; model (2) adds the cross product term of the primary term and secondary term of the intensity of the fracture faultline of the top management team and the degree of corporate performance fallout respectively on the basis of model (1), $fls_{i,t-1}$ represents the intensity of the fracture faultline, and *Control* represents all the control variables.

4. Empirical Results

4.1 Descriptive Statistics

Table 2. Descriptive statistics of the main variables

Variable Name	Sample size	Average value	Standard deviation	Minimum value	Maximum value
RD	1541	9.622	7.473	0.65	41.33
shortfall	1541	0.03	0.063	0	0.346
fls	1541	0.195	0.095	0	0.45
firm age	1541	14.091	5.075	3	31
firm size	1541	21.582	0.983	19.567	24.93
firm nature	1541	0.135	0.342	0	1
unslack	1541	3.451	4.186	0.28	27.56
abslack	1541	0.261	0.163	0.035	1.026
poslack	1541	0.029	0.053	0	0.303
bankruptcy	1541	0.033	0.031	-0.045	0.188
firm opor	1541	2.501	1.671	0.579	13.511
indus oppo	1541	199.322	85.416	12	331
indus RD	1541	7.133	2.219	3.1	11.81
indus opor	1541	2.024	0.752	1.078	4.379

Table 3. Descriptive statistics of manufacturing industry

Variable Name	Sample size	Average value	Standard deviation	Minimum value	Maximum value
RD	1466	2.828	2.088	0	25.310
shortfall	1466	0.023	0.050	0	0.737
fls	1466	0.194	0.106	0	0.557
firm age	1466	13.862	6.061	1	51
firm size	1466	21.638	1.107	13.076	25.217
firm nature	1466	0.368	0.482	0	1
unslack	1466	2.418	5.729	0.05	158.245
abslack	1466	0.318	8.876	0.005	481.706
poslack	1466	0.056	0.086	0	0.599
bankruptcy	1466	0.020	0.194	-8.68	0.853
firm opor	1466	1.977	1.919	0.253	56.664
indus oppo	1466	117.263	76.691	2	223
indus RD	1466	2.757	0.937	0.1	4.460
indus opor	1466	1.613	0.442	0.792	3.995

Table 4. Descriptive statistics of heavily polluting industry

Variable Name	Sample size	Average value	Standard deviation	Minimum value	Maximum value
RD	3116	3.253	2.942	0	52.610
shortfall	3116	0.032	0.763	0	64.690
fls	3116	0.196	0.103	0	0.667
firm age	3116	13.675	5.533	1	38
firm size	3116	8.439	0.464	6.207	9.547
firm nature	3116	21.995	1.350	13.076	27.099
unslack	3116	0.462	0.499	0	1
abslack	3116	2.029	4.498	-0.201	179.578

poslack	3116	0.511	24.204	0	2126.037
bankruptcy	3116	0.082	0.115	0	1.776
firm opor	3116	0.018	0.125	-8.680	0.853
indus oppo	3116	2.010	5.090	0.108	412.341
indus RD	3116	96.382	64.774	2	223
indus opor	3116	2.979	1.070	0.1	5.420

Before regression analysis of the above model, descriptive statistics were first conducted for each variable, and the results are shown in Table 2. From Table 2, it can be seen that the intensity of R&D investment varies greatly among different enterprises, with a maximum value of 41.33 and a minimum value of only 0.65. Compared with manufacturing and heavily polluting industries, the difference in R&D investment in the IT industry is even greater, and the mean value is also higher, which shows that the IT industry pays more attention to R&D investment. Therefore, the IT industry is selected as a more representative sample in this paper.

4.2 Regression Analysis

Table 5. Sample regression results

	(1) RD	(2) RD	(3) RD	(4) RD	(5) RD	(6) RD
shortfall		9.143*	29.771**	30.063**	29.717**	30.013**
		(4.079)	(5.747)	(6.023)	(5.806)	(6.084)
shortfall(sq)			-78.736**	-81.114**	-90.959**	-93.869**
			(15.282)	(16.984)	(19.099)	(20.627)
*fls*shortfall*				27.619		28.230
				(26.566)		(25.404)
*fls*shortfall(sq)*					112.447**	116.856**
					(41.259)	(43.570)
fls	1.060	0.351	0.387	0.342	0.366	0.319
	(0.720)	(0.718)	(0.694)	(0.720)	(0.697)	(0.729)
above aspiration	-8.628	-3.232	2.985	2.645	3.081	2.737
	(6.559)	(7.890)	(7.618)	(7.483)	(7.595)	(7.468)
bankruptcy	49.800**	47.764**	45.495**	45.966**	45.861**	46.358**
	(12.829)	(12.589)	(12.128)	(11.883)	(12.310)	(12.096)
unabsorbed slack	-0.117	-0.101	-0.085	-0.088	-0.088	-0.091
	(0.083)	(0.082)	(0.077)	(0.076)	(0.079)	(0.078)
absorbed slack	-2.240	-1.912	-1.232	-1.218	-1.234	-1.220
	(1.946)	(1.988)	(2.010)	(2.075)	(2.013)	(2.079)
potential slack	4.367*	4.824*	5.011**	5.412**	4.902**	5.308**
	(1.578)	(1.498)	(1.370)	(1.421)	(1.368)	(1.421)
firm age	-0.214	-0.223	-0.236	-0.241	-0.233	-0.239
	(0.177)	(0.178)	(0.174)	(0.180)	(0.177)	(0.182)
firm size	0.638**	0.619**	0.649**	0.645**	0.650**	0.646**
	(0.181)	(0.165)	(0.158)	(0.156)	(0.156)	(0.154)
firm nature	0.121	0.212	0.139	0.107	0.137	0.104
	(0.503)	(0.514)	(0.524)	(0.528)	(0.522)	(0.525)
firm growth opportunity	0.001	0.015	0.016	0.016	0.014	0.013
	(0.042)	(0.040)	(0.032)	(0.032)	(0.032)	(0.032)
industry component	-0.004	-0.004	-0.005	-0.005	-0.005	-0.004
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
industry rd	0.168	0.193	0.162	0.148	0.158	0.144
	(0.117)	(0.111)	(0.105)	(0.094)	(0.105)	(0.093)
industry opportunity	-0.710**	-0.761**	-0.736**	-0.723**	-0.720**	-0.706**
	(0.139)	(0.126)	(0.103)	(0.100)	(0.105)	(0.102)
lag-.rd	0.500**	0.501**	0.497**	0.495**	0.496**	0.495**
	(0.097)	(0.096)	(0.095)	(0.096)	(0.095)	(0.096)
_cons	-5.773	-5.462	-5.980	-5.874	-7.129	-7.066
	(6.272)	(5.752)	(5.120)	(5.193)	(5.397)	(5.486)
year	control	control	control	control	control	control
ind	control	control	control	control	control	control

Obs.	1541	1541	1541	1541	1541	1541

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

In this paper, before conducting the regression analysis, the sample data were first preprocessed in the following steps: to avoid the influence of extreme values, the continuous variables were subjected to tail reduction at the 1% level; the moderating and dependent variables were centered and then cross multiplied into the model operation; the variance inflation factor (VIF) of the relevant variables were tested for multicollinearity, and all of them were below 2, which was much less than the alert value of 10, indicating that this sample The variance inflation factor (VIF) is less than 2, which is much less than the alert value of 10, indicating that there is no serious problem of multicollinearity in this sample.

Model (1) in Table 5 is the baseline model, including all control variables but excluding the independent variable and interaction terms. Model (2) adds the primary term of performance shortfall, and Model (3) incorporates the quadratic term of performance shortfall. Model (4) further includes the interaction term between the primary term of TMT faultline strength and performance shortfall. Model (5) builds on Model (4) by adding the interaction term between the quadratic term of TMT faultline strength and performance lag. Model (6) is the full regression model containing all variables.

Models (2) and (3) are used to test hypothesis 1. From the results of model (2), there is a significant positive linear relationship between the degree of performance lag and R&D intensity, which verifies the reasoning of the theory of firm behavior that as the degree of firm performance lag increases, the intensity of firm R&D increases. However, the results of model (3) show that although the coefficient of the primary term of the degree of disparity is significantly positive, the coefficient of the secondary term is significantly negative, which proves that the relationship between the degree of disparity and R&D intensity is not purely linear: as the degree of disparity increases, the R&D intensity tends to increase and then decrease. However, whether the relationship is an inverted U-shaped relationship or whether the present sample can only represent the curve to the right of the extreme value of the inverted U-shaped relationship needs further statistical verification. Referring to Haans(2016) The existence of the inverted U-shaped relationship is confirmed by the following three indicators: (1) the coefficient of the quadratic term of the degree of performance drop is significantly negative; (2) the slope of the curve is calculated at the extreme value of the range of values of the independent variable in this sample is positive and negative, respectively; (3) the inflection point of the inverted U-shaped curve is 0.180, which is in the value range of the independent variable. All three indicators satisfy the judgment criteria of the inverted U-shaped relationship. On the other hand, Table 5 Models (4) and (6) show that the interaction term between the TMT fracture zone and the performance gap term is not significant, which indicates that the TMT fracture zone moderates the nonlinear relationship between the performance gap and R&D investment rather than the linear relationship, which proves the robustness of the results. Therefore, there is a significant inverted U-shaped relationship between the degree of performance dropout and R&D investment intensity, and hypothesis 1 is confirmed.

The results from models (4) and (5) are used to test Hypothesis 2, focusing on the moderating effect on the inverted U-shaped relationship. This effect can manifest in two ways: first, by shifting the curve horizontally, determined by whether the cross-product term of the independent variable's primary term aligns in sign with the quadratic term; second, by changing the curve's slope. The curve steepens if the quadratic cross-product term has the same sign as the independent variable's quadratic term, and flattens if the signs are opposite. In this sample, the quadratic cross-product term is significantly negative. This indicates that the break band intensity of the top management team flattens the inverted U-shaped curve, weakening the impact of performance decline on R&D investment, thus supporting Hypothesis 2. The full-variance results in model (6) are consistent, partially validating the robustness of the findings.

4.3 Robustness Tests

This paper tests the robustness of the conclusions by the following two methods: first, in addition to the measure of enterprise R&D investment/sales revenue used in this paper, enterprise R&D expenditure/total assets is also a widely used measure of the intensity of enterprise R&D investment, because the ratio of R&D expenditure/total assets normalises R&D investment and is relatively stable, it allows enterprises of different sizes and asset-liability structures to be compared on the same scale. This ratio measurement makes it possible to more intuitively evaluate their relative R&D investment, thereby making the regression results more scientific. Therefore, R&D expenditure/total assets is selected as a proxy for R&D investment. Replacing the measure of the dependent variable is regressed in the same model (Table 6), and the results remain consistent with the conclusions of this paper; second, the performance dropout level measure in this paper The historical expectation is used as the basis of calculation, and the results when the correlation coefficient is 0.6 are selected in the main model for empirical evidence. Referring to related studies, the expectation levels when the correlation coefficient is 0.7 and 0.5 are selected here to calculate the degree of performance lag for the robustness test, and only the regression results when the correlation coefficient is 0.7 are presented in the paper (Table 7). The results of the above robustness tests are not significantly different from the empirical results of this paper. As can be seen from the table 8, the sensitivity of the model to changes in parameters is assessed by changing the upper and lower 10% values of the TMT faultline. The test found that whether the 10% value of the TMT faultline is increased or decreased, the result is still significant, and there is no drastic difference in the coefficient. The sensitivity test is passed, which proves that the selected measurement method is robust

Table 6. R&D expenditure/total assets regression results

	(1) RD	(2) RD	(3) RD	(4) RD	(5) RD	(6) RD
shortfall		0.982	3.095**	3.108**	3.047**	3.022**
		(0.440)	(0.602)	(0.573)	(0.574)	(0.565)
shortfall(sq)			-8.713**	-8.785**	-8.403**	-8.057**
			(1.717)	(1.616)	(1.612)	(1.549)
*fls*shortfall*				1.729		26.503
				(4.707)		(9.761)
*fls*shortfall(sq)*					122.510**	128.482**
					(21.652)	(33.641)
fls	-0.012	0.014	0.063	0.062	0.047	-0.040
	(0.202)	(0.168)	(0.166)	(0.160)	(0.182)	(0.142)
above aspiration	-1.281	-0.661	-0.004	-0.014	0.020	-0.024
	(0.668)	(0.835)	(0.792)	(0.813)	(0.807)	(0.825)
bankruptcy	-0.117	-0.101	-0.085	-0.088	-0.088	-0.091
	(0.083)	(0.082)	(0.077)	(0.076)	(0.079)	(0.078)
unabsorbed slack	-0.350*	-0.312	-0.256	-0.256	-0.258	-0.255
	(0.170)	(0.172)	(0.173)	(0.172)	(0.171)	(0.172)
absorbed slack	0.127	0.183	0.230	0.236	0.219	0.251
	(0.182)	(0.174)	(0.156)	(0.170)	(0.167)	(0.169)
potential slack	-0.026	-0.025	-0.025	-0.026	-0.024	-0.032
	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)	(0.019)
firm age	-0.214	-0.223	-0.236	-0.241	-0.233	-0.239
	(0.177)	(0.178)	(0.174)	(0.180)	(0.177)	(0.182)
firm size	0.044*	0.043*	0.046*	0.045*	0.047*	0.044*
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
firm nature	0.022	0.034	0.028	0.028	0.027	0.028
	(0.051)	(0.053)	(0.054)	(0.053)	(0.053)	(0.052)
firm growth opportunity	-0.007	-0.006	-0.006	-0.006	-0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
industry component	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
industry rd	0.012	0.015	0.013	0.013	0.013	0.011
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
industry opportunity	-0.080	-0.086*	-0.085*	-0.084*	-0.086*	-0.084**
	(0.019)	(0.017)	(0.015)	(0.015)	(0.014)	(0.016)
lag-.rd	0.555**	0.554**	0.550**	0.550**	0.551**	0.552**
	(0.096)	(0.095)	(0.093)	(0.093)	(0.093)	(0.094)
_cons	-0.005	-0.031	-0.123	-0.094	-0.174	0.017
	(0.504)	(0.450)	(0.401)	(0.454)	(0.437)	(0.475)

year	control	control	control	control	control	control
ind	control	control	control	control	control	control
Obs.	1541	1541	1541	1541	1541	1541

Table 7. Regression results at a correlation coefficient of 0.7

	(1) RD	(2) RD	(3) RD	(4) RD	(5) RD	(6) RD
shortfall		10.086	31.694**	31.145**	31.767**	30.904**
		(4.398)	(5.972)	(5.687)	(5.685)	(5.584)
shortfall(sq)			-89.095**	-85.545**	-89.496**	-82.156**
			(17.069)	(15.843)	(16.039)	(15.114)
*fls*shortfall*				-25.828		-29.464*
				(20.885)		(26.859)
*fls*shortfall(sq)*					109.581*	159.203**
					(47.427)	(41.536)
fls	0.388	0.666	1.169	0.994	1.163	0.136
	(2.255)	(1.907)	(1.893)	(2.083)	(1.854)	(1.718)
above aspiration	-11.812	-5.420	1.305	1.584	1.248	1.154
	(6.937)	(8.542)	(8.072)	(8.226)	(8.278)	(8.401)
bankruptcy	-0.112	-0.009	-0.085	-0.088	-0.088	-0.091
	(0.083)	(0.082)	(0.077)	(0.076)	(0.079)	(0.078)
unabsorbed slack	0.190**	0.193**	0.195**	0.195**	0.195**	0.195***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
absorbed slack	-2.724	-2.319	-1.743	-1.759	-1.739	-1.736
	(1.919)	(1.965)	(1.977)	(1.965)	(1.973)	(1.977)
potential slack	1.208	1.782	2.261	2.130	2.293	2.447
	(1.869)	(1.756)	(1.600)	(1.697)	(1.744)	(1.775)
firm age	-0.306	-0.299	-0.299*	-0.287	-0.304	-0.368*
	(0.175)	(0.169)	(0.163)	(0.167)	(0.177)	(0.185)
firm size	0.515*	0.500*	0.531**	0.541**	0.529**	0.515**
	(0.173)	(0.159)	(0.150)	(0.158)	(0.160)	(0.169)
firm nature	0.130	0.254	0.191	0.177	0.194	0.188
	(0.533)	(0.546)	(0.556)	(0.551)	(0.550)	(0.539)
firm growth opportunity	0.001	0.013	0.011	0.014	0.010	0.007
	(0.045)	(0.043)	(0.035)	(0.035)	(0.036)	(0.038)
industry component	-0.005	-0.004	-0.005	-0.004	-0.005	-0.004
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
industry rd	0.129	0.160	0.142	0.139	0.142	0.124
	(0.114)	(0.108)	(0.104)	(0.105)	(0.104)	(0.106)
industry opportunity	-0.661**	-0.725**	-0.707**	-0.724**	-0.704**	-0.703**
	(0.133)	(0.123)	(0.105)	(0.101)	(0.101)	(0.109)
lag-.rd	0.516**	0.514**	0.510**	0.510**	0.510**	0.512**
	(0.098)	(0.096)	(0.095)	(0.095)	(0.095)	(0.096)
_cons	-0.636	-0.915	-1.855	-2.442	-1.699	-0.573
	(6.040)	(5.554)	(4.954)	(5.307)	(5.541)	(5.858)
year	control	control	control	control	control	control
ind	control	control	control	control	control	control
Obs.	1541	1541	1541	1541	1541	1541

Table 8. Sensitivity analysis of TMT faultlines

	(1) RD	(2) RD	(3) RD
shortfall	30.013**	30.873**	30.629**
	(6.084)	(6.948)	(6.796)
shortfall(sq)	-93.869**	-78.088**	-85.473**
	(20.627)	(15.163)	(15.728)
*fls*shortfall(sq)*	116.856**		
	(43.570)		
*fls_plus10*shortfall(sq)*		115.476**	
		(42.364)	
*fls_minus10*shortfall(sq)*			128.912**
			(33.246)
above aspiration	2.737	-3.479	-3.478
	(7.468)	(2.365)	(2.364)
firm age	-0.239	-0.133***	-0.133***
	(0.182)	(0.036)	(0.036)
firm size	0.646**	0.405**	0.405**
	(0.154)	(0.158)	(0.158)
firm nature	0.104	1.420**	1.420**
	(0.525)	(0.554)	(0.554)
unabsorbed slack	-0.091	-0.106*	-0.106*
	(0.078)	(0.060)	(0.060)
absorbed slack	-1.220	33.587***	33.587***
	(2.079)	(0.821)	(0.821)
potential slack	5.308**	-2.015	-2.015
	(1.421)	(2.080)	(2.080)
bankruptcy	46.368***	43.298***	43.298***
	(12.096)	(8.812)	(8.812)
firm growth opportunity	0.013	0.022	0.022
	(0.032)	(0.067)	(0.067)
industry component	-0.004	0.006	0.006
	(0.004)	(0.002)	(0.002)
industry rd	0.144	0.326	0.326
	(0.093)	(0.073)	(0.073)
industry opportunity	-0.706**	-0.072	-0.072
	(0.102)	(0.132)	(0.132)
lag-.rd	0.495**	0.609***	0.608***
	(0.096)	(0.113)	(0.112)
_cons	-7.066	-10.745***	-10.745***
	(5.486)	(3.227)	(3.227)
year	control	control	control
ind	control	control	control
Obs.	1541	1541	1541

5. Further Analysis

This paper only examines the impact of the "presence" of TMT faultlines on the relationship between performance disparity and R&D intensity but does not explore in detail the possible differential impact of different types of characteristic fracture faultlines. It has been found that not all team fractures have a negative impact and that certain subgroups of fractures related to team resources and task performance (e.g., tenure, educational background, etc.) can have a positive impact on team decision-making. (Carton & Cummings, 2012;

Richard et al., 2019) First, the fracture faultlines formed based on these characteristics represent the existence of diverse knowledge and information in the team, which can broaden the team's information base(Richard et al., 2019) Second, the similar knowledge background makes subgroup members formed based on these characteristics understand each other's ideas and intentions better, and they dare to express their ideas and suggestions openly when they expect someone to support them, which is conducive to the formation of a good information sharing atmosphere. (Rupert et al., 2016) Third, unlike the characteristic fracture faultlines related to social identity and interpersonal identity (e.g., gender, age), the subgroups formed by these characteristic fracture faultlines tend not to have relational conflicts and even actively seek out their own identity. even actively seek professional counseling from other subgroups. The subgroups formed by this identity fracture tend not to have relationship conflicts and even actively seek professional advice from other subgroups (Chung et al., 2015). Therefore, to be able to observe as objectively as possible the differential consequences of the different types of subgroups in this sample, it is necessary to focus directly on the subgroups formed by each characteristic fracture faultline.

Given that the fracture faultline strength measure proposed by Shaw in 2004 can calculate the strength of the fracture faultline of each feature in the feature combination and can take into account the degree of consistency of each feature within a subgroup and the degree of consistency of each feature among different subgroup members, whereas Thatcher's (2003) The former method is used as a measure of the strength of fracture faultlines in this paper. The first step is to evaluate the intra-subgroup consistency (IA, with values ranging from 0 to 1), which reflects the degree of similarity among subgroup members on features other than the focal feature; the second step is to calculate the inter-subgroup consistency (CGAI, with values ranging from 0 to 1), which reflects the consistency among subgroups on features other than the focal feature; the third step is to Calculate the fracture faultline intensity on the focal feature $Fls=IA\times(1-CGAI)$. The higher the final calculated break-band intensity, the higher the likelihood that team members form substantial subgroups based on the classification of that feature

Table 9. Regression results for Shaw's measurements

	(1) RD	(2) RD	(3) RD	(4) RD	(5) RD	(6) RD	(7) RD	(8) RD
shortfall	30.825**	30.803**	31.090**	30.354**	30.971**	31.576**	31.394**	31.319**
	(5.982)	(6.005)	(6.134)	(5.698)	(6.072)	(6.124)	(6.099)	(5.842)
shortfall(sq)	-86.838**	-85.795**	-88.726**	-83.865**	-85.197**	-109.017**	-104.919**	-166.625**
	(16.876)	(16.640)	(18.116)	(15.789)	(16.707)	(21.610)	(20.438)	(42.260)
*agefls*shortfall(sq)*		131.480						-42.027
		(109.385)						(96.874)
*genderfls*shortfall(sq)*			73.602					126.826
			(90.114)					(103.261)
*edufls*shortfall(sq)*				-111.646				-199.094
				(116.400)				(110.378)
*tenfls*shortfall(sq)*					124.345**			75.158**
					(32.556)			(21.048)
*spefls*shortfall(sq)*						-157.495**		-133.038*
						(42.196)		(55.794)
*funfls*shortfall(sq)*							-501.518**	-605.048**
							(112.733)	(141.404)
above aspiration	-0.182	-0.239	-0.347	0.058	-0.048	0.049	0.060	0.413
	(7.884)	(7.899)	(7.842)	(8.024)	(7.848)	(7.797)	(7.801)	(7.759)
lag-.rd	0.552**	0.553**	0.552**	0.552**	0.551**	0.552**	0.552**	0.553**
	(0.094)	(0.093)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.093)
genderfls	0.316	0.247	0.326	0.339	0.267	0.247	0.250	0.384
	(0.776)	(0.732)	(0.765)	(0.798)	(0.773)	(0.776)	(0.774)	(0.776)
agefls	0.607	0.622	0.512	0.485	0.781	0.812	0.830	0.471
	(1.630)	(1.636)	(1.647)	(1.589)	(1.644)	(1.630)	(1.630)	(1.602)
edufls	0.543	0.499	0.417	0.414	0.739	0.759	0.776	0.262
	(1.660)	(1.646)	(1.657)	(1.808)	(1.760)	(1.793)	(1.789)	(1.890)
tenfls	184.372	178.559	184.685	182.314	188.466	188.826	188.813	180.353

	(168.211)	(170.331)	(167.741)	(171.114)	(163.498)	(163.493)	(165.351)	(205.372)
funfls	-211.424	-204.817	-211.955	-209.219	-216.273	-216.579	-216.721	-208.721
	(193.004)	(195.433)	(192.491)	(196.148)	(187.736)	(187.743)	(189.732)	(233.586)
spefls	22.956	22.617	23.635	22.958	24.168	24.084	24.544	28.677
	(23.304)	(23.407)	(23.342)	(23.317)	(23.239)	(23.240)	(23.131)	(22.490)
absorbed slack	-2.702	-2.687	-2.705	-2.710	-2.704	-2.715	-2.727	-2.948
	(1.709)	(1.712)	(1.727)	(1.699)	(1.712)	(1.713)	(1.708)	(1.666)
unabsorbed slack	-0.596	-0.511	-0.585	-0.488	-0.485	-0.491	-0.431	-0.401
	(0.099)	(0.092)	(0.097)	(0.094)	(0.072)	(0.074)	(0.079)	(0.098)
potential slack	2.392	2.394	2.577	2.278	2.268	2.277	2.255	2.452
	(1.683)	(1.677)	(1.757)	(1.799)	(1.701)	(1.693)	(1.698)	(1.943)
firm age	-0.247	-0.245	-0.252	-0.236	-0.246	-0.246	-0.245	-0.234
	(0.158)	(0.159)	(0.161)	(0.162)	(0.160)	(0.161)	(0.161)	(0.165)
firm size	0.461**	0.463**	0.460**	0.469**	0.464**	0.466**	0.466**	0.477**
	(0.114)	(0.115)	(0.116)	(0.123)	(0.113)	(0.112)	(0.113)	(0.130)
firm nature	0.282	0.276	0.274	0.269	0.281	0.278	0.279	0.250
	(0.571)	(0.567)	(0.572)	(0.564)	(0.570)	(0.569)	(0.569)	(0.565)
firm growth opportunity	-0.061	-0.059	-0.061	-0.059	-0.064	-0.065	-0.065	-0.063
	(0.039)	(0.040)	(0.039)	(0.040)	(0.037)	(0.037)	(0.037)	(0.042)
industry component	-0.002	-0.001	-0.002	-0.001	-0.002	-0.002	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
industry rd	0.128	0.127	0.122	0.125	0.123	0.124	0.124	0.127
	(0.111)	(0.111)	(0.106)	(0.112)	(0.110)	(0.109)	(0.109)	(0.106)
industry opportunity	-0.852**	-0.855**	-0.844**	-0.866**	-0.834**	-0.829**	-0.827**	-0.827**
	(0.155)	(0.152)	(0.148)	(0.146)	(0.158)	(0.157)	(0.157)	(0.128)
_cons	-1.647	-1.860	-1.611	-2.114	-1.752	-1.785	-1.795	-2.368
	(3.946)	(4.090)	(4.030)	(4.329)	(3.997)	(4.011)	(4.020)	(4.793)
year	control	control	control	control	control	control	control	control
indus	control	control	control	control	control	control	control	control
Obs.	1541	1541	1541	1541	1541	1541	1541	1541

Consistent with the use of the econometric model in the previous section, Table 9 applies Shaw (2004) regression results under the measure of fracture faultline intensity. Model (1) is used to test the robustness of hypothesis 1, and the inverted U-shaped relationship between the degree of performance disparity and R&D intensity still exists when changing the measure of fracture faultline intensity of the top management team; models (2) to (7) add the cross product of the quadratic terms of fracture faultline intensity and degree of performance disparity for each characteristic based on model (1), respectively. The cross product coefficients of the age, gender, and education fracture are not significant, while the cross product coefficients of the tenure fracture are significantly positive, and the cross product coefficients of the professional and functional background fracture are significantly negative, indicating that the age, gender, and education fracture of the top management team do not play a moderating role in this sample, while the tenure fracture negatively moderates the relationship between the degree of performance disparity and the intensity of corporate R&D investment, making the inverted U-shaped curve become The tenure fracture negatively moderates the relationship between the degree of performance disparity and the intensity of corporate R&D investment, making the inverted U-shaped curve flat.

The above results suggest that there are indeed differences in the role played by different characteristic fracture faultlines. Based on the information processing perspective, the tenure, functional background, and educational characteristics fracture bands are expected to have positive moderating effects, but this is not fully evidenced in this sample, and the tenure fracture shows negative moderating effects inconsistent with theoretical expectations, probably because each characteristic fracture band plays different roles in different task and institutional contexts. There are differences in the way subgroups formed by the characteristic fracture bands interact in different task environments, and the degree of conflict among subgroups formed under the same characteristic classification may also vary when top management teams explore different issues, resulting in a decision-making agenda that is not always as difficult to advance. Longer-tenured executives have been found to be more inclined to reduce R&D investment for private gain relative to newer or shorter-tenured executives (Zona, 2016), which may lead to differences in attitudes and opinions among subgroups formed based on tenure when discussing innovation issues, manifesting as relational conflicts that affect the decision-making process; and differences in institutional environments may also lead to differences in the significance of certain characteristic fracture bands Some scholars believe that this is related to the culture of the country, for example, the impact of characteristic fracture faultlines such as gender and age is much more pronounced in Japan than in the United States (Hutzschenreuter & Horstkotte, 2013) Some scholars believe that this is related to the culture of the country.

In addition, it is also evident from Table 9 that the break formed based on gender, age, and education did not have a significant impact, which may be due, on the one hand, to the fact that all three characteristics are relatively superficial, and related scholars have argued that the salience of superficial characteristics decreases over time, as team members get to know each other, and even lose the possibility of forming (Van Peteghem et al., 2018). On the other hand, the relatively deeper fracture faultlines of characteristics related to task processing (tenure, functional background, and specialization) in this sample are more likely to form substantive subgroups and influence team processes; on the other hand, they may be related to the "activation" of fracture lines by the task environment. Specifically, when no task environment mobilizes the interactive behavior of a characteristic subgroup, it may be difficult for the relevant characteristic fracture faultlines to form substantive subgroups and be "activated", just as the tenure-based subgroup may be activated when discussing pension benefits, and tenure-based subgroups may not be actually formed and influenced without the presence of the relevant issue. Without the presence of the issue in question, tenure-based subgroups may not actually form and have an impact (Lau & Murnighan, 1998).

6. Conclusion and Insights

6.1 Conclusion

This paper empirically examines the relationship between the degree of performance disparity and the intensity of corporate R&D investment with the data of listed companies in the IT industry from 2007 to 2018 and investigates the moderating effect of TMT faultlines on this relationship from the perspective of fracture faultline theory. The following conclusions are drawn: the relationship between the degree of performance disparity and the intensity of R&D investment is inverted U-shaped, and the intensity of R&D investment increases and then decreases with the increase of the degree of performance disparity; the relationship between the degree of performance disparity and the intensity of R&D investment is negatively regulated by the fracture faultline of the top management team, and the conflict from the fracture faultline leads to inefficient decision making and reduces the intensity of R&D investment, which makes the relationship between the degree of performance disparity and the intensity of R&D investment more stable. The further study of TMT faultlines shows that among the combinations of fracture faultline characteristics selected in this study, gender, age, and education fracture faultlines do not show significant effects, while tenure fracture faultlines show significant negative moderating effects and professional and functional background fracture faultlines show significant positive moderating effects, which indicates that different This suggests that the effects of different trait fractures are different and that the same trait fracture may produce differential results across task settings and groups when compared to existing research on trait types.

In conclusion, this study recommends that firms should tailor their R&D investment strategies to the extent of their performance shortfall. For minor gaps, increasing R&D investment may drive breakthrough solutions. However, as the performance shortfall grows and risks the firm’s stability, a conservative approach to R&D can help mitigate unnecessary risks and safeguard the firm’s longevity. Additionally, companies should strategically structure their top management teams, considering the effects of team faultlines. Strong faultlines can slow decision-making, so when a firm’s performance declines, board adjustments to the executive team should focus on creating a balanced mix of characteristics. The aim is to avoid deep fractures within the team, promoting both harmony and diversity to reduce subgroup formation and internal conflicts. Lastly, different types of faultlines impact team dynamics in varying ways. Tenure-based faultlines tend to increase conflicts, so minimizing tenure divisions in the executive team is advised. In contrast, faultlines based on professional backgrounds can enhance information sharing and decision efficiency, supporting smoother strategic adjustments. Thus, companies should consider factors like gender, age, tenure, and education to strengthen the team’s decision-making efficiency and adaptability during change.

The contribution of this paper is to introduce the top management team fracture band theory in order to explore how top management team fracture bands affect the relationship between performance fallout and the intensity of corporate R&D investment, enriching the application of higher order theory in corporate strategic change. At the same time, the article further explores the differential impact of subgroups formed based on different characteristics by combining two different fracture faultline measures by Thatcher (2003) and Shaw (2004) and expands the research perspective of fracture faultline theory.

6.2 Shortcomings and Prospects

The limitations of this paper include: (1) since the sample is only drawn from the IT industry, the applicability of the findings in other industries needs to be proved by subsequent studies; besides the limitations of the sample, since the effect of the fracture faultline is influenced by the task context. In the future, the relationship between team faultlines and different types of strategic change in enterprises can be further studied. For example, research can be conducted on the impact of team fault lines on resource-consuming and resource-releasing strategies. this paper only explores the task context of corporate R&D investment decision, while the effect of the team fracture faultline in other task contexts may show opposite findings. Future research can focus on the differential effects of different industries and task contexts on the fracture faultlines for exploratory research; In recent years, environmental protection has received sustained attention from the government and the public. Future research can be expanded to include heavily polluting industries and clean industries to see if different conclusions can be drawn. Research results may also vary under different external and internal conditions, such as the degree of market competition and different government regulations. (2) the executive characteristics selected in this paper do not take into account certain localized elements that may have important effects, such as hometown relationship and party membership, which have very profound effects in the Chinese context and are worth further exploration and research in the follow-up.

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