R&D Intensity and Stock Price Crash Risk: Based on OLS Multivariate Linear Regression

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Abstract—This study investigates the impact of research and development intensity, the ratio of R&D expenditures, and the total assets of the firm (RDI) on stock price crash risk. To get the relationship between RDI and crash risk, this study uses multiple linear regression (OLS) on panel data of firms listed on SHSE and SZSE in China. The results show that RDI is positively associated with stock price crash risk. They are still robust after conducting a series of robustness tests, such as alternating a dependent variable and adding control variables. Further analyses display that the impact of RDI on crash risk is more significant for the firm with fewer independent directors, non-big 4 auditors, non-outside auditors, and higher analyst attention and reports. The findings in this study support notion that increasing RDI appears to increase stock price crash risk.

Keywords: Research and development intensity; Stock price crash risk; China

1 INTRODUCTION

The National Bureau of Statistics in China shows China's research, and development intensity increased from 104.249 billion yuan in 2001 to 2.4426 trillion yuan in 2020. The percentages of R&D expenditures and GDP are 0.94% and 2.40%, respectively. The investment in research and development in China has increased about 22 times. The patents application also increases from 11,191 to 801,135 at the same time, according to the data from World Bank. With innovation activities increases, R&D expenditures have become an important topic in China nowadays. The capital market also pays a lot of attention to technologies companies. The three biggest Chinese companies listed in the US stock market are ALIBABA(BABA) with $429.364 billion, JINGDONG(JD) with 99.183 billion, and PINDUODUO(PDD) with 96.867 billion (dated 2021/8/21). According to their fourth-quarter financial report in 2020, BABA suffers an increased adjusted EBITA loss because of increasing investments in technological research and innovation. JD disclosed an increased R&D intensity by 25.4% from the third quarter of 2020 to the fourth quarter. PDD had an R&D intensity of 6.8917 billion yuan which increases by 78% compared with last year, and the occupation of R&D intensity and revenue is 11.6%. From the data disclosed in their financial reports, most companies pay a lot of attention to research and development.

Given the macro and micro attention of the research and development, a question arises whether the R&D intensity has a positive effect on the stock market's performance. Prior scholars have researched the determinants of stock volatility from spillover [1], firm size, book-to-market ratio, momentum, liquidity, cash flow-to-price ratio, and returns on assets [2] and macroeconomic factors [3]. Considering its importance and significance, there is a relative lack

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of research on the association between R&D intensity and stock performance, especially for stock price crash risk.

Kothari [4] raises that innovation investment may bring uncertainty of future revenue, which is higher than the investment on fixed assets. Firms should cautiously tradeoff between research and development investment and revenue [5]. With higher investment in innovation, Kim [6], Ball [7], and Verrecchia [8] assumed that management would withhold the bad news the innovation activities may cause due to their selfish motives. This information asymmetry may also deviate stock price may from equilibrium, thus increasing the probability of crash risk [9]. In addition, Hoffmann and Broekhuizen [10] point that new investment products are often specifically developed and marketed to appeal to such needs [11], and highly involved consumers are likely to be more attracted to these innovations. From behavior finance, Fang and Li [12] indicate that irrational investors may impact information disclosure negatively, which promotes the accumulation of negative news of corporate and the probability of price falling suddenly may increase. In a nutshell, high research and development intensity may increase information asymmetry, then enlarging crash risk.

This study supplements the gap by examining the effect of R&D intensity and crash risk applying collected data, including the R&D intensity of each firm listed in SHSE and SZSE in China from 2007 to 2020. The result shows that R&D intensity is significantly positively associated with stock price crash risk, which is also robust to several robustness checks, including alternating the other dependent variable and adding more independent variables. Further analyses show that the impact of R&D intensity is more pronounced in firms with fewer independent directors, non-big 4 auditors, non-outside auditors, higher analyst attention, and more analyst reports.

This study contributes to the extant literature in three ways. First, this study is within the leading part of research on the association of R&D intensity and stock price crash risk. The findings provide support the notion that R&D intensity appears to increase the crash risk of firms. Second, this study contributes to the reference for R&D intensity and crash risk in emerging countries. Most existing research on R&D intensity or crash risk collects data are from developed counties. However, the data researched in this paper are collected in an emerging country. The reason for choosing China as a research background is it invests a lot of assets in research and development. From 2007 to 2020, China experiences an explosion of R&D investment, and its intensity increases by 22 times, which is a good setting for research. Moreover, individual investors in the Chinese capital market are large and irrational and have weak corporate control [13]. This study also contributes to understanding the impact of R&D intensity on crash risk in an irrational stock market.

The remainder of this study is organized as follows. This study develops the hypothesis in Section 2. The research design, including the construction of the sample, model, and variables, is described in Section 3. Empirical analyses are discussed in Section 4, and robustness checks are in Section 5. Further analyses are performed in Section 6. Section 7 concludes the study.

2 HYPOTHESES DEVELOPMENT

Prior studies argue that cumulative bad news withheld by management could increase information asymmetry, thus increase stock price crashes once the withhold excess a tipping point [13, 14]. Previous literature examined the determinants of crash risk of stock price, including CEO centrality [15], corporate customer concentration [16], corporate innovation strategy [17], investor protection [18] as well as institutional investors [19, 20]. In conclusion, information disclosure is beneficial to reduce the crash risk of stock price and decrease the tendency that cumulative bad news reaches the tipping point.

For corporate innovation, exploratory firms are more prone to stock crash risk, which may incur a higher failure-to-success ratio [17]. Additionally, exploratory firms would create patents with higher information and technology barriers, thus increasing information asymmetry [21]. In addition, Huberman and Regev [22] also raised that exploratory can attract more investors, which may increase the stock price. Kahneman [23] pointed that investors' attention is a rear resource, and it may cause pricing bias in the market [24], thus finally increasing crash risk in the future.

The other view is that investors may pay more attention to firms with high innovation activities. Hoffmann and Broekhuizen [10] point that innovation is attractive since new products appeal to such needs, thus attracting more people. More attention to people on stock makes the public interpret corporate information more efficiently and decreases future crash risk [14]. Therefore, this study proposes two competing hypotheses about firm innovation.

H1a: R&D intensity has a significantly positive impact on crash risk, other things being equal.

H1b: R&D intensity has a significantly negative impact on crash risk, other things being equal.

3 RESEARCH DESIGN

3.1 Construction of sample

The initial sample in this study comprised all firms listed in SHSE and SZSE in China from 2007 to 2020. It comprises down to up volatility over fiscal year (*DUVOL*), annual R&D expenditure, and total assets. This study divides R&D expenditure by total assets to measure firm-specific research and development intensity, which can be referred to as *RDI*, and ignores the impact of firm size. The reason for choosing 2007 as the beginning year of the sample is because the first R&D expenditure of the firm is recorded in that year. All the data was collected from annual reports via China Stock Market Accounting Research (CSMAR) system. Finally, the usable sample comprised 24,913 observations, representing 3,605 firms with R&D expenditure.

3.2 Models

The hypotheses to be tested are the stock price crash risk is a function of *RDI*. The basic empirical model applied is:

$$DUVOL_t = \beta_0 + \beta_1 RDI_t + \sum_{q=2}^{m} \beta_q (qth\_ControlVariable_t) + \varepsilon_t \tag{1}$$

where β_1 represents regression coefficients; β_0 stands for the regression coefficient of, and ε_t is an error term. A positive (negative) β_1 indicates a trend of increasing (decreasing) the stock price crash risk. β_q are relative regression coefficients for other control variables, and $DUVOL_t$ is the measure of stock price crash risk in year *t*.

3.3 Variables

3.3.1 Dependent variable: stock price crash risk

Following Yuan [13], Chen [25], and Kim [6], this study employs one firm-specific crash risk $DUVOL_t$. It is measured based on firm-specific weekly returns (donated by W). According to Yuan [13] and Kim [6], it may derive from the following:

$$r_{i,t} = \alpha_i + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \varepsilon_{i,t} \tag{2}$$

Where $r_{i,t}$ is the return of stock *i* in week *t*, and $r_{m,t}$ is the value-weight of stock market return in week *t*; $\varepsilon_{m,t}$ is the residual in Eq. (2). The firm-specific weekly returns in week *t*, $W_{i,t}$ could be calculated as the logarithm of one plus the residual return in the past, $W_{i,t}=\ln(1+\varepsilon_{i,t})$.

Down-to-up volatility (*DUVOL*) could be calculated as [13]

$$DUVOL_{i,t} = \log\{[n_u - 1] \sum_{Down} W_{i,t}^2]/[(n_d - 1) \sum_{Up} W_{i,t}^2]\} \tag{3}$$

where n_u and n_d are the numbers of up and down weeks. The up weeks is the week *t* where the return of stock *i* is higher than its annual average return in that year. The down weeks is the week *t* where the return of stock *i* is lower than the mean in that year [13, 6]. *DUVOL* also corresponds to the crash risk of stock positively.

3.3.2 Test variable: R&D intensity

This study employs R&D intensity (*RDI*) to measure the innovation capability of firms. As this study mentions before, the equation of *RDI* could be

$$RDI_{i,t} = R\&D\ Expenditures_{i,t} / Total\ Asset_{i,t} \tag{4}$$

where $RDI_{i,t}$ represents R&D intensity of stock *i* in year *t*; $R\&D\ Expenditures_{i,t}$ is R&D intensity of stock *i* in year *t*, and $Total\ Asset_{i,t}$ is the total asset of stock *i* in year *t*. The latter two variables can be found in the annual financial report of each firm.

3.3.3 Control variables

We control several factors that have been shown to have an impact on the future crash risk of the stock price in prior studies. Chen [25] reports book-to-market ratio could impact crash risk because of stochastic bubbles. This ratio corresponds to crash risk negatively. Therefore, this study controls the book-to-market ratio (BM_t), which is the ratio of the book value of stock and market value of it. Following Yuan [13], Hutton [14], and Chen [25], this study also controls for Size ($SIZE_t$), the natural logarithm of the book value of total assets in year t, and the book value of total assets of each firm could be collected in their annual financial reports. This study also controls for return on asset (*ROA_t*), which is referred to as net profit divided by the book value of total assets in year *t* [13]. The final control variable is the annual ratio of research and development intensity and the firm's total revenue (*RDR_t*).

4 EMPIRICAL ANALYSES

4.1 Descriptive statistics

Table 1 provides descriptive statistics for the variables researched in this study. After depleting extreme values of data, the mean of a dependent variable, $DUVOL_t$ is -0.1902, and that of the test variable, RDI_t, is 0.0271, which is similar to Yuan [13]. For other control variables, the average of BM_t, ROA_t, $SIZE_t$, RDR_t are 0.3528, 0.0388, 21.7560, and 0.0899, respectively, in line with Yuan [13] and Krishnamurti [15].

Table 1 Descriptive statistics. This table reports descriptive statistics on $DUVOL_t$, and RDI_t, from 2007 to 2020 and other control variables, BM_t, ROA_t, $SIZE_t$, RDR_t.

Variable	Obs.	Mean	Std.dev	Minimum	50%	75%	Maximum
$DUVOL_t$	21,571	-0.1902	0.4908	-2.3271	-0.1929	0.1221	3.4270
RDI_t	21,571	0.0272	0.0271	0	0.0218	0.0360	0.7571
BM_t	21,571	0.3528	0.2010	-0.5369	0.3154	0.4707	0.9598
ROA_t	21,571	0.0388	0.1080	-5.4637	0.0377	0.0711	1.7223
$SIZE_t$	21,571	21.7560	1.1044	17.5753	21.6224	22.3530	28.2516
RDR_t	21,571	0.0899	0.1247	0	0.0488	0.0983	0.9709

4.2 Correlation analysis

This study calculated Pearson correlation coefficients between variables. The correlation coefficient between RDI_t and crash risk measure is significantly positive at level 10%, and most of the correlations between the independent variables are relatively low. To further analyze the existence of multicollinearity of these independent variables, this study computed the variance inflation factor (VIF) for these independent variables, and the results are shown below:

Table 2 Correlation matrix. This table reports the correlation coefficients of 6 variables and their significance level.

	$DUVOL_t$	RDI_t	BM_t	ROA_t	$Size_t$	RDR_t
$DUVOL_t$	1.0000					
RDI_t	0.0120*	1.0000				
BM_t	-0.0141**	-0.1921***	1.0000			
ROA_t	-0.0050	0.0792***	-0.0750***	1.0000		
$Size_t$	-0.1072***	-0.1005***	0.3877***	0.0391***	1.0000	
RDR_t	-0.0119*	0.4333***	-0.0834***	-0.0716***	-0.0262***	1.0000

*** stands for p value < 1%, **stands for p value < 5%, *stands for p value < 10%

Table 3 Variance inflation factors of each independent variable.

Variables	VIF
$DUVOL_t$	1.1553
RDI_t	2.5712
BM_t	4.5604
ROA_t	1.1603
$Size_t$	6.7974
RDR_t	1.8994

The largest VIF for independent variables is 6.7974, and the smallest one is 1.1553, the scale of which is much smaller than the rule of thumb cutoff of 10.00 raised by Kennedy [26]. Therefore, the conclusion is that multicollinearity may not have a serious impact on this regression.

4.3 Regression analysis

The first column of Table 4 performs the simple regression between RDI_t and $DUVOL_t$. The second column indicates the regression adding control variables. The coefficient of RDI_t is 0.4414 and significant at 1% when it is the only independent variable in the regression. With control variables, the coefficient of RDI_t and $DUVOL_t$ is 0.6102, still significant at the 1% level. According to Wu and Chen [27], the R&D intensity is positively associated with absolute idiosyncratic volatility. Firms with a higher level of idiosyncratic volatility are more likely to experience a crash in stock price [28].

Table 4 Regression result of Eq (1), (6). Column (1) displays the result of simple regress only between $DUVOL_t$, and RDI_t and Column (2) reports the regression of Eq (1), both of which are empirical analyses. For robustness check, Columns (3), (4), and (5) provide the result of regression using an alternative dependent variable without and with control variables and Eq (7).

	$DUVOL_t$	$DUVOL_t$	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$
RDI_t	0.4414***	0.6102***	0.4644***	0.5184**	0.5048***
	(0.000)	(0.000)	(0.009)	(0.019)	(0.007)
BM_t		0.0667***		-0.0023	0.1320***
		(0.000)		(0.938)	(0.000)
ROA_t		-0.0085		-0.0426	-0.0636*
		(0.789)		(0.388)	(0.056)
$SIZE_t$		-0.0125***		-0.0034	-0.0011
		(0.000)		(0.511)	(0.764)
RDR_t		-0.0477		-0.0240	-0.0711**
		(0.115)		(0.6410)	(0.021)
Lev_t					-0.0468**
					(0.020)
$TobinQ_t$					0.0264***

					(0.000)
Cash$_t$					0.1195***
					(0.000)
Constant	-0.2926***	-0.0436	-0.4070***	-0.3294***	-0.2959***
	(0.000)	(0.204)	0.000	(0.003)	(0.000)
Observations	22,216	21,571	22,216	21,571	21,571
Adjusted R^2	0.001	0.001	0.000	0.000	0.008

*** stands for p value < 1%, **stands for p value < 5%, *stands for p value < 10%

5 ROBUSTNESS CHECKS

In this part, the study performs several robustness checks, including adopting an alternative dependent variable, adding control variables to make multivariate regression.

5.1 Alternative a dependent variable

Yuan [13], Kim [6], and Chen [25] indicate negative conditional skewness of firm-specific weekly returns over the fiscal year (*NCSKEW*) is also the measure of crash risk. It is calculated by the equation as

$$NCSKEW_{i,t} = -[n(n-1)^{\frac{3}{2}} \sum W_{i,t}^{3}]/[(n-1)(n-2)(\sum W_{i,t}^{2})^{\frac{3}{2}}] \tag{5}$$

where *n* is the number of the total trading week on stock *i* in year *t*. $NCSKEW_t$ corresponds to the crash risk of stock positively.

This study also makes regression between $NCSKEW_t$ and RDI_t, and the regression equation is shown as

$$NCSKEW_t = \beta_0 + \beta_1 RDI_t + \sum_{q=2}^{5} \beta_q (qth\_ControlVariables) + \varepsilon_t \tag{6}$$

where β_0 is the intercept of the regression and $_1$ is the residual of the Eq. (6) Positive (Negative) represents that $NCSKEW_t$ would increase with RDI_t increases (decreases).

The result in Table 4, Columns 3 and 4 are the simple regression and that with the control variables of the regression with the independent variable of $NCSKEW_t$. Column 3 finds the coefficient is 0.4644, significant at 1% level. The positive association between RDI_t and $NCSKEW_t$ maintains when adding other control variables, and Column 4 indicates the coefficient is 0.5184.

5.2 Adding control variables

To check the regression result of Eq (1), the study adds more variables to make a new function as

$$DUVOL_t = \beta_0 + \beta_1 RDI_t + \sum_{q=2}^{6} \beta_q (qth\_ControlVariables) + \beta_7 Lev_t + \beta_8 TobinQ_t + \beta_9 Cash_t + \varepsilon_t \tag{7}$$

Following Yuan [13], new adding control variables are leverage (Lev_t), the ratio of the book value of debt, and the book value of the total asset of a firm in year t. Tobin's Q value ($TobinQ_t$), the sum of equity capitalization and debt capitalization divided by total assets at the fiscal year t end and the sum of cash and short-term investments scaled by total assets in year t ($Cash_t$) raised by James [29]. These data are collected from China Stock Market Accounting Research (CSMAR) system. In column 6, the result indicates the coefficient of RDI_t and $DUVOL_t$ is 0.5048, significantly positive at level 1%. The coefficients of ROA_t, $Size_t$, and Lev_t are all significantly negative.

The coefficients of the control variables are generally consistent with prior studies [13]. Firms with higher returns, lower book-to-market ratios, lower leverage, and lower ROA are associated with higher future crash risk.

6 FURTHER ANALYSES

Following Yuan [13], this study also discusses the situation with monitoring mechanisms, including board independence, big 4 auditors. Besides, other mechanisms such as analyst attention and reports [30] and outside auditors are also important. This part would discuss the regression under ten environments: more independent directors and less independent directors; big 4 auditors and non-big 4 auditors; outside auditors and non-outside auditors; more analyst attention and less analyst attention; more analyst relative reports and less analyst relative reports. All data are collected from 2007 to 2020 via China Stock Market Accounting Research (CSMAR) system. The first discussion assesses the impact of independent directors of a company on the relationship. This study would also explore auditors' influence on the company about RDI_t and $DUVOL_t$, which would be divided into the classifications of big 4 auditors and outside auditors. The final part would discuss whether the external analysis would indicate a trend between RDI_t and $DUVOL_t$. This study classifies big 4 auditors, the number of independent directors and outside auditors, analyst attention, and reports as a stronger monitoring mechanism. The rest indicators are included in the weaker monitoring mechanism. The result is shown in Table 5.

Table 5 Regression result of Eq (6) in stronger monitoring mechanisms and weaker monitoring mechanisms.

Dependent	**Stronger monitoring mechanisms**					**Weaker monitoring mechanisms**				
	More independent directors	***Big 4 auditors***	***Outside auditors***	***Higher analyst attention***	***More analyst reports***	***Fewer independent directors***	***Non-Big 4 auditors***	***Non outside auditors***	***Lower analyst attention***	***Fewer analyst reports***
	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$	$DUVOL_t$

RDI_t	0.6185**	1.2315**	0.6221	0.4244***	0.4005***	0.3863***	0.4019***	0.4369***	0.1194	0.1726
	(0.019)	(0.016)	(0.549)	(0.002)	(0.003)	(0.002)	(0.001)	(0.000)	(0.546)	(0.403)
Constant		-0.3133	-0.3114	-0.2549	-0.2589	-0.2840	-0.2915	-0.2921	-0.3158	-0.3156
		(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,763	1,321	442	10,142	10,601	18,456	21,207	21,773	12,073	11,614
Adjusted R^2	0.001	0.005	-0.001	0.001	0.001	0.000	0.001	0.001	-0.000	-0.000

*** stands for p value < 1%, **stands for p value < 5%, *stands for p value < 10%

As shown above, this study predicts that a weaker monitoring mechanism is more significant to strengthen the crash risk of the stock when there are fewer independent directors, non-big 4 auditors, and non-outside auditors. However, higher analyst attention and more reports under stronger monitoring mechanisms also represent a causality between RDI_t and crash risk.

6.1 More independent directors and less independent directors

Independent director is an important component of corporate control. Corporate transparency increases in independent director tenure,[29] which may reduce information asymmetry to prevent cumulative bad news from reaching a tipping point and finally reduce crash risk. For those higher than the median, three, they would be labeled as a sample of more independent directors. The other would be labeled as a sample of less independent directors.

The result indicates that RDI_t significantly predicts $DUVOL_t$ under the circumstance of fewer independent directors, and the coefficient is 0.3863 at the 1% level. Because of the principal-agent mechanism, the management, who take command of internal information advantage of companies, would have more interest conflict with stakeholders. Major shareholders would occupy the interest of minor shareholders, such as related party transactions, misappropriation of public funds, and therefore causing higher crash risk [31]. The existence of independent directors would increase corporate transparency [29]. Thus, fewer independent directors would have serious information asymmetry or even agent conflict, finally making the crash risk more significant.

6.2 Big 4 auditors and non-big 4 auditors

Big 4 auditors are external monitoring of corporate and assist firms in disclosing financial information frequently, which is beneficial for decreasing information asymmetry and impacts on crash risk. This study assumes a dummy variable to define it. The firm with big 4 auditors as and the one without big 4 auditors as 0. The coefficient of RDI_t with big 4 auditors is 1.2315 at the 5% level, and that with non-big 4 auditors is 0.4019 at the 1% level. Table 5 shows RDI_t impact significantly on crash risk if the companies have non-big 4 auditors. This may indicate that non 4 big auditors would increase the information asymmetry, making the crash risk more significant.

6.3 Outside auditors and non-outside auditors

Besides, outside auditors are also vital to information symmetry. This study also defines the firm with outside auditors as 1 and those which with non-outside auditors as 0. The result represents those non-outside auditors would significantly increase the crash risk since the coefficient is 0.4019 at the 1% level. Outside auditors assist corporate transparent their information, which would reduce the cumulative information asymmetry and crash risk [6, 9]. Combined with the result discussed in 6.2. part, the study may conclude that outside and serious auditors could decrease information asymmetry of corporate and decrease crash risk as well.

6.4 Higher analyst attention and lower analyst attention

Table 5 reports that higher analyst attention would significantly increase the crash risk of the stock. The coefficient of higher analyst attention is 0.4244 at the 1% level. Analysts may collaborate with firms to public false information to disturb the market and make the stock more volatile, thus increasing crash risk. [30]

6.5 More analyst reports and lower analyst reports

To strengthen the conclusion gained from 6.4. analysis, this study also changes the other monitoring mechanism, analyst reports, to make a double-check. From Table 5, the coefficient of RDI_t under higher analyst attention is significant at 0.4005. Compared with lower analyst reports, higher reports may explore more information and increase the probability that the public gets bad news from corporate, then serious the crash risk.

7 CONCLUSIONS

In general, this study researches the impact of RDI_t on crash risk and finds that RDI_t appears to increase crash risk in the future. After a series robustness check, the result is still pronounced, including alternating a dependent variable and adding control variables, Lev_t, $TobinQ_t$, and $Cash_t$. This study extends prior studies on crash risk by analyzing RDI_t and $DUVOL_t$ in different situations classified by independent directors, big 4 auditors, outside auditors, analyst attention, and analyst reports. As RDI_t increases, it could indicate the crash risk, especially when there is a shortage of external information disclosure. However, the higher analyst attention and reports indicate that the collaboration between analysts and firms exists, making false information published and increasing stock price crash risk.

The results in this study also implicate that corporate should evaluate the R&D intensity cautiously since it would increase the crash risk of the stock. For supervisors, R&D intensity will be a good indicator of crash risk, and related policies could be made to supervise the market. R&D intensity is an important consideration when investors make the transaction, and they should be cautious about firms which high R&D intensity.

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