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The Impacts of Research and Development In Artificial Intelligence (AI) Industry on Company's Financial Risk Control In China

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Abstract

Artificial Technology in financial area has triggered a hot discussion about its influence. Previous research proved that the relationship between AI technology and company's stock risk control can be either positive or negative. Our research will demonstrate whether its impact in China's company is positive or negative. We collect thousands of companies' data, which using Research and Development (R&D) expense as the proxy of inputs of AI and volatility as the proxy of stock risk of companies to test the hypothesis. And I use a regression equation to demonstrate the impact of RD to volatility, as a consequence, I find that RD and volatility has a negative relationship, while volatility is more driven by other factors, such as ROA, financial leverage and total market value. This study combines AI with financial risk and uses data to demonstrate the thesis statement later, which can be regarded as empirical research. So it has value and is supportive to develop further research of the relationship between these two variables.

JEL Classification: G32, G34, G17

Keywords: Artificial Intelligence (AI), corporate financial risk, risk control

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1. Introduction

Nowadays, a digital revolution is spread over the whole world, which was led by Artificial Intelligence (AI). Digitalization has transformed the entire human world of industry. In the digital age, consumers have become Internet users (Khmiadashvili, 2019). Artificial Intelligence is an important infrastructure of digital economy under the new situation, with the ability to combine with various industries. What's more, more and more industries and fields are upgrading intelligently at different levels. The new AI era will cover far more than the traditional understanding of the Internet and science and technology industries, which will bring productivity and connectivity to the whole society (Scherer, 2015). AI is growing and developing rapidly, and the collaboration between humans and AI has brought crucial achievements to enterprises (Khmiadashvili, 2019).

Digital finance is through the use of the Internet technology, with the aid of computer information processing, data communication, data analysis, a series of relevant technologies such as cloud computing applications in the financial sector, promote information sharing, and effectively reduce the transaction cost and the threshold of financial services, expand the scope of financial services and coverage (Koh et al., 2018). With the advantages of digital finance sharing, convenience, security, low cost, and low threshold, the technology of big data, cloud computing, and artificial intelligence is used to build a data-based risk control system, so as to comprehensively improve the risk control ability of finance. Within the definition of digital finance, it really focuses on the reduction of financial risk, which will better facilitate the growth and improvement of risk management. Digital inclusive finance well interprets the original intention

and goal of fintech. It is a digital way for people who have long been excluded from modern financial services to enjoy formal financial services (Koh et al., 2018).

Most of the ordinary people, lacking assets and an adequate credit system, are hardly able to borrow enough money from traditional commercial banks, nor can they expand the production of these funds (Hasan et al., 2020). From the market situation of China, China has sixty million to seventy million small business owners and merchants, from 120 million to 150 million low-income earners, rural residents from 180 million to 200 million, who are the long tail market of commercial bank mouth. They lack perfect credit reporting portrait, sufficient collateral, plus the height of the geographical dispersion. If the organization wants to provide financial services, it is necessary to invest huge manpower and extremely complex information data collection, mid-term credit review, and post-loan management (Yang and Zhang, 2020). For commercial banks, the single transaction amount of such customers is small, but the cost is unusually high, which is quite different from the large enterprises and large customers that commercial banks serve. As a result, commercial banks are almost unwilling to invest in ordinary small and micro customers (Hasan et al., 2020). This is the main dilemma and challenge of the background of the financial market, as well as the reason for the emerge of digital finance.

So under the situation of the current market and the rapid development of Artificial Intelligence, the applications of AI is significant for the improvement of the market. The development of AI and apply it in the financial area enables financial institutions of all kinds to obtain more information about borrowers through cutting-edge digital technologies, improve the accessibility of financial resources, reduce the cost of financial services, and improve the financing efficiency of small and micro enterprises (Mhlanga, 2020). Therefore, the application of AI has a huge impact on financial risk control and management.

And after testing my regression model, RD has a negatively significant relationship with ROA, while it has a positively significant relationship with financial leverage. In terms of ROA, it has a greatly significant relationship with financial leverage, which is negative. And it has a positively significant relationship with total market value. Moreover, financial leverage has a greatly significant relationship with total market value, which is positive. Additionally, after using various models to test my results and conducting robustness check, I find that my results of different models are all consistent with my findings in the previous parts, and I can say that it is appropriate when applying to these methods. And the main finding I have concluded is that RD and volatility has a negative relationship, while volatility is more driven by other factors, such as ROA, financial leverage and total market value. Because when considering these control variables, the significance of independent variable has greatly changed, which from little significant to not significant. And from my various regression test methods, I also find that total market value has a relatively big influence on volatility.

The contribution of this study is reflected in these aspects. Firstly, there are humorous studies focus on AI technology in financial areas, and I select one specific field to express and demonstrate the impacts of AI in more detailed. What's more, the risk is a really important factor for financial institutions and companies, so this study can provide a more beneficial reference for the research of this period. Thirdly, this study combines AI with financial risk and uses data to demonstrate the thesis statement later, which can be regarded as empirical research, so it has value and is supportive to develop further research of the relationship between these two variables.

The remainder of the paper proceeds as follows. Section 2 reviews related literature and develops hypotheses. Section 3 describes the data. Section 4 describes the sample and variable

construction, and the different models to test the findings. Section 5 is the whole conclusion to the findings and the thesis.

2. Literature Review and Hypotheses Development

The relationship between the application of AI technology and risk control and management has a fierce discussion in the financial field. The impact is not simplex, while triggers the different opinion about this. Therefore, we review relevant theories and previous articles in the following sections.

2.1. Positive Effects of R&D in AI Technology on China Company's Financial Risk Control

Previous research had studied the various AI application in financial risk management because of their efficiency and low cost, which can help to improve the risk management of not only financial organizations but also companies (Arsic, 2021). In this article, the author found that AI techniques can be applied in various aspects in financial sectors, such as quality assurance, text-mining for the purpose of data augmentation, and so on, which will become an important part of the process of financial risk management. What's more, because the traditional financial risk management means are costly and time-consuming, the combination of AI technology and financial risk management can provide more efficient applications for companies, which can bring more efficiency and confidence within such a business environment in recent years (Arsic, 2021). Therefore, they focused on an opinion that there is little barrier to AI technology in financial risk

management, which can offer in-time information to the companies that are exposed to the financial risk and provide them advanced management methods.

And another research also found that the application of AI technology has been applied in the financial field and played a significant role in terms of this. Wu (2021) put forward that AI technology can improve the ability to deal with risks. Finance support is really vital for the development of the companies, which means that financial decisions will generate a direct and wide impact on the growth of the company. During the period of its development, the company should increase the ability to respond the risk through various practices, such as AI technology is an excellent example. Through the use of AI, the company can better monitor the financial condition and control their decision, and then enhance the risk management consequently (Wu, 2021).

Thach et al. (2021) have emphasized that AI technology makes our society step into industry 4.0, which brings significant impacts to the banking system in some merging markets. For example, when AI technology applies to the banking system and makes some changes to its activities models, such as using the cloud to store data or increasing online transactions, banks will plan to risk management. And authors used Korea as an example to demonstrate that some banks became the most effective businesses that focusing finance in this country through combining AI technology and information-security service or products (Thach et al., 2021). They reflected that AI technology will bring a lot of benefits to the banks, such as reduce the cost and time, improve efficiency, and so on, which will reduce the risk finally.

Lomakin et al. also talked about the relationship between AI inputs and financial risk, especially focused on stock and securities. They found that the use of AI technology can help to hedge stock risks, which can promote the accuracy of stock price and reduce the volatility

(Lomakin et al., 2020). Zheng et al. (2019) also showed that the combination financial area and AI technology can create more wisdom, which embodies in assets management, risk management and so on. Wilkens (2019) insisted her opinion that chine learning has become an important tool in quantitative finance, while it is still not so systematic is financial risk field. Ha et al. (2019) also found that compared with original P2P lending, the application of AI technology in a model to assess credit risk has played an crucial role to improve investment efficiency. Moreover, Gu et al. (2018) represented that it simplified the stock pricing through machine learning, which highlighted the essential status of AI technology in reduction of stock price volatility. Jia and Stan (2021) have used startup company as the example to illustrate the benefits of usage of AI technology to facilitate the reduction of company risks. Wang et al. (2020) established a model to test this impact, and they found that AI model could better forecast the volatility in the market and promoted information structure.

Based on the above discussions, AI technology is positively related to financial risk control and management, embodying on reduced potential or existing risks, improve the variety of risk management methods, or reduce financial activities cost and time. We therefore propose our first hypothesis.

Hypothesis 1: *R&D in AI technology has a positive impact on financial risk control.*

2.2. Negative Effects of R&D in AI Technology on China Company's Financial Risk Control

In the modern world, businesses should adopt to some changes such as the new technology to help them maintain their current position, which can also help to gain competitive advantages

among their rivals. Behind this background, Tohănean et al. (2020) presented that bringing AI technology into the company's business model will put it at high risk. They explained that not only because of the flexibility of the middle-sized company, which make them make the business decision more rapidly and accept the implementation of AI technology more easily, but also this kind of companies depend on the financial cash flows to a great extent, therefore they are more sensitive to the market change (Tohănean et al., 2020). For the sake of various aspects of reasons, the application of AI technology in their business activities may trigger a higher level of risk to them.

Another research also indicated the disadvantages of AI technology to financial risk. In this article, the author focused his study field on the credits market, and he emphasized that the use of AI technology will bring shortages to the credit market, which means increasing financial risk, especially systemic financial risk (Odinet, 2021). Odinet (2021) also explained that the application of AI means that the company should build its AI capability, which will increase the complexity. Johnson (2015) also presented that cyber technology posed a significant threat to financial market, nd it would create systemic risk, which did increased the financial volatility.

What's more, three authors put forward their idea together that AI inputs could disrupt the financial system, create new tail risks, and worse existing risks due to various external factors (Danielsson et al., 2021). Leo et al. (2019) also studied that although machine learning has already been applied in many risk control fields, it still has a lot of shortages, which may not so effective in financial risk control. Murugesan and Manohar (2019) said that AI will undermine the financial system of the future because it is disrupting the job market and financial risk, and it may not so applicable in financial area because the knowledge and skills in this filed is really lacking.

Based on the above discussions, AI technology is negatively related to financial risk control and management. We therefore propose our second hypothesis.

Hypothesis 2: *R&D in AI technology has a negative impact on financial risk control.*

3. Data and Methodology

3.1. Data

The data of study majorly comes from Bloomberg, I obtain equities from 840 different companies from various industries which are all related to AI technology. In the original report, it reflects each equity's name, price-to-earnings ratio, revenue, price, earnings per share, total market value and gross return. What's more, I download other data types, such as registration date, return of equity, return of assets, financial leverage, research and development expenses, debt-to-equity ratio, total market value and volatility. The sample period is from 12 months from 2019 to 2020 and all data are monthly, because the data I mentioned before is usually calculated based on the previous year. After obtaining these data, the research and development expenses can be regarded as the input and cost of AI technology, which is the independent variable in the study, and volatility is the measurement of financial risk in this study, which is the dependent variables. Except for these two variables, the other data obtained Bloomberg can be seen as control variables, which are the other factors can have the impacts to the outcome of the study. For example, P/E ratio is market value per share divided by earnings per share, earnings per share is net income divided by end-of-period common shares outstanding. Moreover, total market value (OMV) is calculated by multiplying a company's outstanding shares by its current market price, ROE is net income divided

by average shareholder's equity, ROA is net income divided by total assets, and financial leverage is long-term debt divided by total assets. Volatility is a measurement of the difference in returns for a given security. On most circumstances, the volatility is higher, it means that the security is risker. Volatility is usually measured by the standard deviation, or variance, among returns on the same security.

3.2. Methodology

First, according to Chen et al. (2018), if we use WACC, the cost of capital, or the beta of the CAPM to substitute the various variables of a company's financial risk, these measurements are more easily affected by market risk, which will trigger some incorrect outcomes or the bias to the results. Therefore, we use CAPM to calculate the residuals and then use the method presented by Ang et al. (2006), who used standard deviation of the numerical value calculated in CAPM regression to measure the financial risk (Chen et al., 2018).

In order to better understand the relationship of AI technology and financial risk of the company, we use the method based on one previous method put forward by Li and Sethi (2021) to examine the impacts of these two variables.

$$Volatility_{it} = \alpha + \beta_{1i} RD_{it} + \beta_{2i} ROA_{it} + \beta_{3i} Lev_{it} + \beta_{4i} OMV_{it} + \varepsilon_{it} \quad (1)$$

where $Volatility_{it}$ is the proxy of financial risk, which is dependent variable and usually measured by the standard deviation, or variance, RD_{it} is the proxy of AI inputs that is independent vairable, and ROA_{it}, Lev_{it}, and OMV_{it} are the control variables in this regression model, which are net income divided by total assets, long-term debt divided by total assets, a company's outstanding shares multiplied by its current market price respectively, and ε denotes the residuals of the firm.

4. Results and Discussions

4.1. Main Results

Our regression is Equation (1), which is shown in Table 3. We consider all variables, including independent variables and control variables, as well as dependent variables.

We find that when we just consider independent variable and dependent variable, p-value for the coefficient on X is 0.054, so it is a little significant. we can see that Line Fit Plot shows that the fitting line deviates from the original datasets by large amounts, so I cannot claim that X is equal to R and D has a negative impact on Y is equal to Volatility. Once the ROA, financial leverage and total market value are taken into account, note that P-value for the coefficient on X, X_1, X_2 and X_3 is equal to 0.1284, 0.2640,0.1280 and 0.0735 respectively. We can see that the coefficient on R and D is not significantly different from 0, whose p-value is 12.84%. In contrast, the control variable ROA, financial leverage, and total market value are not significant or a little significant, while the coefficient on R and D switches from little significantly negative to not significantly negative. The larger the ROA, the larger volatility. And the larger financial leverage or total market value, the lower volatility. The higher R and D, the lower volatility. So the change of significance of independent variable shows that volatility is mainly driven by Financial Leverage and total market value, and more investment in R and D actually reduces firm financial risks.

We find that our results are not statistically significant, but economically significant. If we multiply coefficient by the expected value of X, the result has a large economic magnitude. If we multiply coefficient by the standard deviation of X, we can also have a large economic magnitude.

So we can claim that the impact of R and D on Volatility is not statistically significant, but it is economically significant.

4.2. Additional Results

4.2.1 Quantile Regression

Unlike conventional linear regression, which uses the least square method to calculate the conditional mean of the target under different eigenvalues, quantile regression estimates the conditional median of the target. It means that quantile regression is an extension of linear regression, which is more useful than variance methods. In this table, we can also draw the conclusion like previous tables, which is *OMV* mainly drive the change of *Volatility* and is more significant than independent variable *RD*.

4.2.2 Interval Regression

Interval regression is used to simulate results with interval truncation. In other words, you can know which ordered category each observation belongs to, but we don't know the exact value of the observation. Interval regression is a generalization of truncated regression. While from this table, we cannot exactly judge the relationship between these variables, because the observation is different from previous ones. And the confidence value in this regression is greatly lower, we can say that this regression is not an excellent for my study.

4.2.3 Multivariate Regression

Multivariate regression can be useful when there are different variables while it is a single regression model. So I change the equation assumption to test the feasibility of my regression. From this table, the observation outcome is consistent with earlier tables, which is *OMV* has more significant impact to our dependent variable.

4.3. Robustness Checks

4.4.1 Robustness Check of Linear Regression

Robustness test examines the robustness of the evaluation method and indicator interpretation ability, that is, whether the evaluation method and indicator still maintain a relatively consistent and stable interpretation of the evaluation results when some parameters are changed. And in this table, we can find that after changing some parameters, the robust standard error is relatively small in terms of *RD, ROA, Lev and OMV*, which means that the conclusion we draw from the previous section is in a stable condition. And in this table, we can find that *OMV* has great impact to dependent variable, which means that we have more confidence to say it.

4.4.2 Robustness Check of Mixed-Effects Regression

A linear model needs to meet the assumptions of normality, independence, linearity and homoscedasticity, among which independence is one of the most important assumptions of a linear model. Independence requires that every data point must come from a different population. However, because repeated measurement data, block data and spatial correlation data cannot satisfy the independence hypothesis, linear mixed effects model is often used to analyze the above

data. According to this table, we can see that z value varies differently in terms of different variables, so we cannot directly regard this regression as a good one. And according to this table, the robust standard error of various independent variables is a little small. So we can say that the conclusion is also appropriate when applying to mixed-effects regression.

5. Conclusions

After testing my regression model, RD has a negatively significant relationship with ROA, while it has a positively significant relationship with financial leverage. In terms of ROA, it has a greatly significant relationship with financial leverage, which is negative. And it has a positively significant relationship with total market value. Moreover, financial leverage has a greatly significant relationship with total market value, which is positive. Additionally, after using various models to test my results and conducting robustness check, I find that my results of different models are all consistent with my findings in the previous parts, and I can say that it is appropriate when applying to these methods. And the main finding I have concluded is that RD and volatility has a negative relationship, while volatility is more driven by other factors, such as ROA, financial leverage and total market value. Because when considering these control variables, the significance of independent variable has greatly changed, which from little significant to not significant. And from my various regression test methods, I also find that total market value has a relatively big influence on volatility.

Artificial Intelligence is an important infrastructure of digital economy under the new situation, with the ability to combine with various industries. With the advantages of digital finance

sharing, convenience, security, low cost, and low threshold, the technology of big data, cloud computing, and artificial intelligence is used to build a data-based risk control system, so as to comprehensively improve the risk control ability of finance. Under this background, I devoted to study the relationship between AI inputs and financial risk control. My research demonstrates whether inputs in AI technology impact in China's company's financial risk is positive or negative. I collect thousands of companies' data, which using Research and Development (R&D) expense as the proxy of inputs of AI and volatility as the proxy of stock risk of companies to test the hypothesis. After conducting this study, I think that my paper can contribute to this field to help people know that the other important factors can influence volatility.

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Table 1: Sample Statistics of Risk of Companies Using AI Technology

The table reports descriptive statistics for the sample of companies who have used AI technology and their trends of financial change from the last 12 months:

$$Volatility_{it} = \alpha + \beta_{1i} RD_{it} + \beta_{2i} ROA_{it} + \beta_{3i} Lev_{it} + \beta_{4i} OMV_{it} + \varepsilon_{it},$$

where *RD* is the proxy of AI inputs, and *ROA*, *Lev* and *OMV* are the control variables in this regression model, *Volatility* is the financial risk, and ε denotes the residuals of the firm. All of these data are obtained from Bloomberg and calculated by Excel. In this table, DE Ratio is the measurement of financial risk, *RD* is the proxy of AI inputs, and *ROA*, *Lev* and *OMV* are the control variables in this regression model. Moreover, ROA is net income divided by total assets, Financial Leverage is long-term debt divided by total assets, and total market value is a company's outstanding shares multiplied by its current market price.

Variables	**Number of Observation**	**Mean**	**StDev**	**Min**	**Max**	**Skewness**	**Kurtosis**
Volatility	840	45.956	19.943	12.375	119.112	0.551	-0.113
RD (Billion)	840	0.331	1.618	0	34.250	0	0
ROA	840	4.961	6.865	-43.589	39.294	-0.644	8.224
Lev	840	2.967	9.705	1.028	267.185	24.569	659.722
OMV (Billion)	840	16.960	52.809	1.049	122.443	0	0

Table 2: Correlations

The table shows the correlations between our independent variable and control variables through using thousands of Chinese companies.

$$Volatility_{it} = \alpha + \beta_{1i} RD_{it} + \beta_{2i} ROA_{it} + \beta_{3i} Lev_{it} + \beta_{4i} OMV_{it} + \varepsilon_{it}$$

where *RD* is the proxy of AI inputs, and *ROA*, *Lev* and *OMV* are the control variables in this regression model. ROA is net income divided by total assets, Financial Leverage is long-term debt divided by total assets, and Total Market Value is a company's outstanding shares multiplied by its current market price. The table shows that *RD* has a little positive correlation with *OMV*, *Lev* has a little negative correlation with *ROA*.

	RD	***ROA***	***Lev***	***OMV***
RD	1			
ROA	-0.042** (-1.227)	1		
Lev	0.035** (1.019)	-0.100*** (-2.92)	1	
OMV	0.159 (4.656)	0.031** (0.888)	0.007*** (0.200)	1

Table 3: Main Regression Results

The table shows the results of the regression:

$$Volatility_{it} = \alpha + \beta_{1i} RD_{it} + \beta_{2i} ROA_{it} + \beta_{3i} Lev_{it} + \beta_{4i} OMV_{it} + \varepsilon_{it},$$

where *RD* is the proxy of AI inputs, and *ROA*, *Lev*, and *OMV* are the control variables in this regression model, *Volatility* is the financial risk, and ε denotes the residuals of the firm. What's more, we use different signs to indicate different degree of p-value, which can reflect the level of significance. * means that p-value is between 5% and 10%, ** means that p-value is between 1% and 5%, and *** means that p-value is less that 1%. Robustness test examines the robustness of the evaluation method and indicator interpretation ability, that is, whether the evaluation method and indicator still maintain a relatively consistent and stable interpretation of the evaluation results when some parameters are changed. And in this table, we can find that after changing some parameters, the robust standard error is relatively small in terms of *RD, ROA, Lev and OMV*, which means that the conclusion we draw from the previous section is in a stable condition. And in this table, we can find that *OMV* has great impact to dependent variable, which means that we have more confidence to say it.

Variables	*Volatility*
RD	-0.655**
	(-2.18)
ROA	0.112
	(0.8)
Lev	-0.108***
	(-2.95)
OMV	-0.024***
	(-3.38)
# of observation	840
Adjusted R-square	0.013

Table 4: Mixed-Effects Regression

The table shows the results for the in-sample regression:

$$Volatility_{it} = \alpha + \beta_{1i} RD_{it} + \beta_{2i} ROA_{it} + \beta_{3i} Lev_{it} + \beta_{4i} OMV_{it} + \varepsilon_{it},$$

where *RD* is the proxy of AI inputs, and *ROA*, *Lev*, and *OMV* are the control variables in this regression model, *Volatility* is the financial risk, and ε denotes the residuals of the firm. A linear model needs to meet the assumptions of normality, independence, linearity, and homoscedasticity, among which independence is one of the most important assumptions of a linear model. Independence requires that every data point must come from a different population. However, because repeated measurement data, block data and spatial correlation data cannot satisfy the independence hypothesis, linear mixed effects model is often used to analyze the above data. According to this table, we can see that z value varies differently in terms of different variables, so we cannot directly regard this regression as a good one. And according to this table, the robust standard error of various independent variables is a little small. So we can say that the conclusion is also appropriate when applying to mixed-effects regression.

Variables	*Volatility*
RD	-0.655 (-1.53)
ROA	0.112 (1.12)
Lev	-0.108 (-1.53)
OMV	-0.024** (-1.8)
# of observation	840
Adjusted R-square	0.029

Table 5: Quantile Regression

The table shows the results for the in-sample regression:

$$Volatility_{it} = \alpha + \beta_{1i} RD_{it} + \beta_{2i} ROA_{it} + \beta_{3i} Lev_{it} + \beta_{4i} OMV_{it} + \varepsilon_{it},$$

where *RD* is the proxy of AI inputs, and *ROA*, *Lev*, and *OMV* are the control variables in this regression model, *Volatility* is the financial risk, and ε denotes the residuals of the firm. Unlike conventional linear regression, which uses the least square method to calculate the conditional mean of the target under different eigenvalues, quantile regression estimates the conditional median of the target. It means that quantile regression is an extension of linear regression, which is more useful than variance methods. In this table, we can also draw the conclusion like previous tables, which is *OMV* mainly drive the change of *Volatility* and is more significant than independent variable *RD*.

Variables	*Volatility*
RD	-0.51
	(-0.87)
ROA	0.004
	(0.03)
Lev	-0.667
	(-0.69)
OMV	-0.016**
	(-0.9)
# of observation	840
Adjusted R-square	0.066

Table 6: Interval Regression

The table shows the results for the in-sample regression:

$$Volatility_{it} = \alpha + \beta_{1i} RD_{it} + \beta_{2i} ROA_{it} + \beta_{3i} Lev_{it} + \beta_{4i} OMV_{it} + \varepsilon_{it},$$

where *RD* is the proxy of AI inputs, and *ROE*, *ROA*, and *Lev* are the control variables in this regression model, R^F is the financial risk, which will be measured by the debt-to-equity ratio, and ε denotes the residuals of the firm. Interval regression is used to simulate results with interval truncation. In other words, you can know which ordered category each observation belongs to, but we don't know the exact value of the observation. Interval regression is a generalization of truncated regression. While from this table, we cannot exactly judge the relationship between these variables, because the observation is different from previous ones. And the confidence value in this regression is greatly lower, we can say that this regression is not an excellent for my study.

Variables	*Volatility*
RD	-0.655
	(0.26)
ROA	0.112
	(1.12)
Lev	-0.108
	(-1.53)
OMV	-0.013
	(0.13)
# of observation	840
Adjusted R-square	0.046

Table 7: Multivariate Regression with Other Variables

The table shows the results for the in-sample regression:

$$Volatility_{it} = \alpha + \beta_{1i} RD_{it} + \beta_{2i} ROA_{it} + \beta_{3i} Lev_{it} + \beta_{4i} OMV_{it} + \varepsilon_{it},$$

where *RD* is the proxy of AI inputs, and *ROE*, *ROA*, and *Lev* are the control variables in this regression model, R^F is the financial risk, which will be measured by the debt-to-equity ratio, and ε denotes the residuals of the firm. Multivariate regression can be useful when there are different variables while it is a single regression model. So I change the equation assumption to test the feasibility of my regression. From this table, the observation outcome is consistent with earlier tables, which is *OMV* has more significant impact to our dependent variable.

Variables	*Volatility*
RD	-0.655
	(-1.52)
ROA	0.112
	(1.12)
Lev	-0.108
	(-1.52)
OMV	-0.013*
	(-1.79)
# of observation	840
Adjusted R-square	0.013