

# How Big Data Patents Affect Enterprise Data Technology's Impact on Market Value and Profitability

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# Abstract

This paper explores in detail the impact of enterprise data technology capabilities on market value and profits. Using big data patent statistics closely related to data collection, analysis and application as a measurement standard, the study reveals the positive role of enterprise data technology capabilities in significantly improving market value, especially in the financial and wholesale and retail industries. However, despite the huge potential, most companies still face many challenges in converting this technological advantage into actual profits, and in some cases even have an adverse impact on the profits of industrial enterprises. It is worth noting that industrial internet supplier companies have successfully achieved a double leap in market value and profits with their comprehensive investment in R&D, capital, government subsidies and IT infrastructure. Based on this, the study puts forward a series of suggestions to promote enterprises to strengthen data technology capabilities, increase complementary investments, develop diversified application scenarios and profit models, and further improve data market mechanisms and infrastructure construction to comprehensively promote the effective development and utilization of data. In order to continue to promote the development and utilization of data by various market entities in USA, it is recommended to focus on improving enterprise data technology capabilities, increase complementary investments and profit models for data technology capabilities, increase complementary investments and profit models for data technology capabilities, increase complemented to focus on improving enterprise data technology capabilities, increase complementary investments and profit models for data technology capabilities, increase complementary investments, develop application scenarios and profit models for data technology capabilities, increase complementary investments, and profit models for data technologies, cultivate professional data service institutions, and promo

**Keywords:** Data Elements, Data Technology Capabilities, Complementary Inputs, Big Data Patents, Market Value and Profitability

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# I. Introduction

Since 2010, with the large-scale commercial application of new generation information technologies such as the internet, internet of Things, cloud computing and artificial intelligence, the scale of data resources has grown rapidly and new models as well as new formats of digital economy supported by data have emerged in large numbers. The important status and value creation potential of data as a key production factor have been widely recognized by all sectors of society. It has become a national strategy to establish and improve the institutional mechanisms related to data elements and give full play to the supporting role of data elements in the digital economy. In October 2019, the Fourth Plenary Session of the 19th the federal government of USA adopted the "Decision of the federal government of USA on Several Major Issues Concerning Upholding and Improving the Socialist System with USA Characteristics and Promoting the Modernization of the National Governance System and Governance Capacity", proposing to improve the mechanism for the market to evaluate the contribution of production factors such as labor, capital, land, knowledge, technology, management and data as well as determining remuneration based on contribution, formally establishing the status of data as a production factor.

In January 2022, the State Council issued the "14th Five-Year Plan for the Development of Digital Economy", which clearly stated that the supply of highquality data elements should be strengthened, the marketoriented circulation of data elements should be accelerated and the development as well as utilization mechanism of data elements should be innovated, so as to give full play to the role of data elements. In December 2022, the "Opinions of the The federal government of USA and the State Council on Building a Data Infrastructure System to Better Play the Role of Data Elements" was officially released, providing basic systems and guiding principles for the development and utilization of data elements in terms of data property rights, circulation and transactions, income distribution and security governance. It aims to give full play to USA's advantages such as massive data scale and rich application scenarios, stimulate the value creation potential of data elements and enhance new momentum for the development of the digital economy.

However, from the perspective of the digital transformation practices of enterprises, especially manufacturing enterprises, there are still many practical difficulties and challenges in the development and utilization of data resources as well as the mining and release of the value of data elements. Whether data resources can be truly transformed into data elements depends on whether the enterprise has the corresponding data technology capabilities to extract effective information from the original data and apply it to all aspects of the enterprise's production and operation. After the relevant technical capabilities are formed, whether the enterprise can achieve efficiency improvement and profit growth with the help of data elements is still uncertain, and is subject to many restrictions in the internal capital, technology, management, personnel and other aspects of the enterprise and the external environment. To this end, this paper intends to construct a data patent intensity variable based on literature review and mechanism analysis, using enterprise patent statistics related to data collection, analysis and application, to characterize the data technology capabilities of micro-enterprises, analyze its overall impact on the market value and profits of listed companies and the industry heterogeneity characteristics, and explore the realization path of enterprises using data technology capabilities to improve profits, and provide reference for the effective use of data resources and support for the high-quality development of the digital economy from an empirical perspective.

The subsequent contents of this article are arranged as follows: In the second part, the relevant research on data elements, enterprise data technology capabilities and their impacts is sorted out. On the basis of summarizing the existing research content and conclusions, the research ideas and marginal contributions of this article are proposed. In the third part, the variables and models used in this article are constructed to introduce the empirical analysis ideas. In n the fourth part, the overall impact of enterprise data technology capabilities on market value and profits is analyzed, and the endogeneity problems of key variables are processed and tested. In the fifth part, the industry heterogeneity effects of enterprise data technology capabilities are analyzed, and industrial Internet supplier companies are used as subsamples to explore and analyze the specific mechanisms by which enterprises can achieve profit improvement through data technology capabilities. In the sixth part, research conclusions and policy recommendations str presented.

# **II. Literature Review**

# Data Elements and Enterprise Data Technology Capabilities

The rapid development of new generation information technology has significantly reduced the cost of data collection, storage, processing and use, making it a key production factor in the digital economy era (Bhat & Momaya, 2020). Data have unique technical-economic characteristics, such as non-competitiveness, partial exclusivity, externality and immediacy, which can play a positive role in the economy and society through macro value creation, micro efficiency improvement and R&D innovation promotion. Most theoretical studies support the role of data in promoting economic growth and value creation, with some scholars arguing that raw data are difficult to directly participate in production activities (Cai & Wu, 2024). To be transformed into a real production factor, enterprises must have data technology capabilities, with big data analysis as the core for extracting effective information

Impact of Enterprise Data Technology Capabilities on Market Value and Profits

How to fully mobilize the enthusiasm of market players and promote the development and utilization of data are crucial to exploring the value creation potential of data and effectively giving play to the role of data as a production factor (Floren et. al., 2021). Existing studies have shown that enterprises carried out rich practices in data collection, storage, analysis as well as use and have had a certain improvement effect on performance (Guan et. al., 2021). First, in terms of market value performance, existing studies and practices have shown that the accumulation of corporate data resources and the improvement of data technology help to improve investment market confidence (Hlasny, 2023). The massive data resources and related technical capabilities owned by large technology companies such as Apple, Microsoft, Amazon and Facebook have become their important assets, providing investors with important new indicators for evaluating future income, which can effectively improve market expectations and achieve corporate market value (Hlasny, 2023; Hu et. al., 2021). Secondly, in terms of corporate profitability and other performance indicators, existing studies have tried to use variables such as questionnaires and IT investment to analyze the impact of corporate data resources, data capabilities, etc. on corporate sales revenue, profit level and production efficiency (Huang et. al., 2023; Ji et. al., 2022). Related research has verified the role of corporate data technology capabilities in improving single indicators, but lacks a systematic assessment of corporate market value and profits (Khunakornbodintr, 2024).

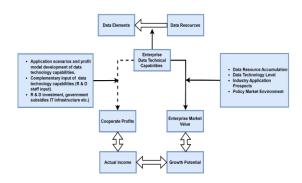
# Enterprise Data Technology Capabilities and Complementary Investments

Data technology capabilities are essential for transforming data resources into valuable data elements (Kim et. al., 2021). Enterprises need to invest in industry scenario mining and technical support capacity improvement to fully realize the value creation potential of data elements (Lee et. al., 2023). Financial insurance and e-commerce are mature fields for data technology applications, while the manufacturing industry faces challenges like complex data structures, high analysis thresholds, and data security. To fully utilize data technology capabilities, enterprises must continuously improve their technology level, R&D capabilities and make adaptive adjustments in personnel allocation and organizational management (Luo & Zor, 2023; Piekkola, 2020). Factors like decentralized decision-making mechanisms, employee digital skills and data-driven decision-making can help enterprises efficiently develop and utilize data resources (Rahimnia & Molavi, 2021).

# **III. Research Ideas**

This paper focuses on the importance of enterprise data technology capabilities in achieving profitability and economic benefits (Ribeiro & Shapira, 2020). It identifies the prerequisites for enterprises to use data technology capabilities to achieve profitability and examines its impact mechanism on enterprise profits (Salas et. al., 2023; Song & Zhao, 2021). The study distinguishes between data resources, data elements and data technology capabilities, focusing on the distinction between raw data resources and production factors (Talafidaryani, 2021). The research uses big data-related patent statistics to construct data technology capability variables, which can more objectively and accurately reflect the development level of enterprise data technology capabilities (Wang et. al., 2021). It also distinguishes the impact of data technology capabilities on enterprise market value as well as profits and examines the industry heterogeneity of related impacts (Wong et. al., 2023). The paper compares and analyzes the results of the impact of data technology capabilities on enterprise market value and profits, exploring its heterogeneous impact on industrial enterprises, financial and wholesale and retail enterprises, and professional service enterprises (Yang, 2021).

The study provides a reference for enterprises to transform data technology capabilities into profitability by analyzing the impact path of data technology capabilities and their complementary inputs on enterprise profits (Yang et. al., 2020). The research selects a sub-sample of companies likely to achieve profits by relying on data technology capabilities and analyzes the effects as well as mechanisms of the impact of data technology capabilities and related complementary inputs on the sub-sample companies (Yin et. al., 2022). Research ideas on the impact of enterprise data technology capabilities on market value and profits are indicated below.



# Figure 1. Research Ideas on the Impact of Enterprise Data Technology Capabilities on Market Value and Profits

Source: Authors's compilation

# **IV. Research Design**

Sample Selection and Data Sources

This paper uses USA's NYSE U.S. 100 Index top companies from 2009 to 2023 as the research sample and utilizes the number of patent applications as well as authorizations related to corporate data technology capabilities to construct core explanatory variables. After matching patent data with company financial data, 3,849 listed companies were obtained as the initial sample, totaling 28,145 company-year observations. The patent data used in this paper come from the patent database of the State Intellectual Property Office and the financial data of listed companies comes from the Wind Database and the Bloomberg.

#### Variable Construction - Core Explanatory Variables

This paper defines data technology capability as the technical capability of enterprises to transform raw data resources into production factors (data elements) that participate in value creation (Yue & Guo, 2022). With the data service support of the USA Automotive Intellectual Property Investment and Operation Center, we selected the number of patent applications and authorizations directly related to the development and utilization of data elements from the patent database of the State Intellectual Property Office as a measure of enterprise data technology capability. This paper adopts the method of combining the International Patent Classification (IPC) with keyword retrieval and selects a total of 7 patents, namely cloud computing, big data, machine learning, deep learning, knowledge graph, computer vision and natural language processing.

Among them, cloud computing and big data patents reflect the technical capabilities of enterprises in data storage and management. Machine learning, deep learning, knowledge graph, computer vision and natural language processing patents reflect the technical capabilities of enterprises in data analysis and application. In the subsequent empirical analysis, the above 7 patent statistics will be summed up to form a big data patent variable, which is used to characterize the comprehensive technical capabilities of enterprises in big data storage, management, analysis and application.

Based on the original patent data, this paper draws on Zeng et. al.'s (2020) processing method for artificial intelligence technology patent data to calculate the cumulative number of data patent applications and authorizations of enterprises since 2010 and obtain the stock of data patent applications and authorizations, calculate the ratio of patent applications and authorization stocks to total assets of the year, add 1 to the result and take the natural logarithm, so as to obtain the data patent application intensity (data1) and data patent authorization intensity (data2) of the enterprise in that year.

It should be further pointed out that the enterprise data patent intensity variable used in this paper can only reflect the data technology capabilities formed by the enterprise through its own R&D investment and practical accumulation and cannot cover the data technology as well as related services obtained by the enterprise through external procurement or cooperation (Zeng et. al., 2020). Therefore, subsequent empirical research will focus more on how the data technology capabilities acquired by USA's listed companies based on R&D investment and practical accumulation affect their market value and financial performance, and further analyze the impact as well as mechanism of enterprise data technology in different scenarios such as self-use of technology and use of technology for others.

# Variable Construction - Explained Variable

In order to analyze and test the relationship between data technology capabilities and corporate performance (Zhang et. al., 2024), this paper constructs the following two types of explained variables, which respectively represent the performance of listed companies in financial markets and financial returns: (1) Enterprise market value (lntobin) - According to the formula (market value of tradable shares + number of non-tradable shares × net assets per share + book value of liabilities) / total assets, calculate the enterprise Tobin's Q value and take the natural logarithm to measure the financial market value of listed companies.

(2) Corporate profit (Inprofit) - The total profits of listed companies are selected and taken into account the natural logarithm to represent the corporate profit level. At the same time, in the robustness test part, the annual growth rate of corporate operating income (growth) and net profit margin of total assets (ROA) are used to replace the corporate profit variable to test the impact of data patent intensity on other financial indicators such as corporate operating income and profitability efficiency. When regressing corporate market value, corporate profits and net profit margin of total assets will be added to the regression model as control variables.

# Variable Construction - Control Variables

In order to control the impact of non-data technology capability factors such as enterprise characteristics and operating environment on the market value and profits of listed companies, this paper refers to existing research in related fields and constructs the following control variables from the basic information, capital structure, management system, R&D investment and policy support of listed companies. Among them, the basic information variables of listed companies include enterprise size (size), duration (firmage) and state-owned enterprises (SOE). Capital structure variables include asset-liability ratio (lev) and cash flow ratio (cashflow). Management system variables include the number of directors (board), equity concentration (top1), equity checks and balances (balance) as well as the proportion of independent directors (indep). R&D investment variables include R&D personnel investment (lnrdps) and R&D capital investment (Inrdspd). Policy support variables are government subsidies (Ingovsub). At the same time, industry, year and province dummy variables will be added to the regression model to control the trend of industry, year and province changes that affect corporate performance as seen in Table 1.

| Туре                     | Variable | Definition  | Observations | Mean  | Std.<br>Dev. | Min    | Max   |
|--------------------------|----------|---|--------------|-------|--------------|--------|-------|
| Core Explanatory         | datal    | Data patent<br>application<br>intensity           | 28145        | 0.630 | 1.390        | 0      | 8.690 |
|                          | data2    | Data technology<br>strength                       | 28145        | 0.470 | 1.140        | 0      | 8.050 |
| Explained<br>Variable    | Intobin  | Enterprise market<br>value                        | 27311        | 0.590 | 0.480        | -0.130 | 2.270 |
|                          | Inprofit | Enterprise profit                                 | 25391        | 19.11 | 15.32        | -0.610 | 23.87 |
|                          | growth   | Annual growth rate<br>of operating<br>income      | 26304        | 0.210 | 0.550        | -0.620 | 3.880 |
|                          | ROA      | Return on assets                                  | 28145        | 0.050 | 0.080        | -0.260 | 0.210 |
|                          | size     | Enterprise scale                                  | 28145        | 22.24 | 2.160        | 13.76  | 31.14 |
|                          | firmage  | Enterprise age                                    | 28145        | 2.830 | 3.390        | 0      | 4.140 |
|                          | SOE      | State-owned<br>enterprise                         | 28145        | 0.370 | 0.490        | 0      | 1     |
|                          | lev      | Asset-liability ratio                             | 28145        | 0.440 | 0.230        | 0.050  | 0.970 |
|                          | cashflow | Cash flow ratio                                   | 28145        | 0.050 | 0.080        | -0.200 | 0.250 |
| Control Variable         | board    | Board size  | 27999        | 2.150 | 0.480        | 1.100  | 3.050 |
|                          | topl     | Shareholder<br>concentration                      | 28145        | 0.360 | 0.160        | 0      | 0.940 |
|                          | balance  | Shareholding<br>balance                           | 28145        | 0.750 | 0.640        | 0      | 4     |
|                          | indep    | Independent<br>director ratio                     | 27999        | 0.380 | 0.070        | 0      | 0.610 |
|                          | Inrdeps  | R&D personnel<br>input                            | 13674        | 5.460 | 2.190        | 0      | 10.75 |
|                          | Inrdspd  | R&D expenditure                                   | 21482        | 17.74 | 6.620        | 0      | 25.13 |
|                          | Ingovsub | Government<br>subsidy                             | 28145        | 15.57 | 8.110        | 0      | 25.13 |
| Supplemental<br>Variable | datally  | Data patent<br>application<br>intensity (lags)    | 24291        | 0.060 | 0.120        | 0      | 0.970 |
|                          | data2lv  | Data technology<br>strength (lags)                | 24291        | 0.030 | 0.070        | 0      | 0.480 |
|                          | dtl      | Data patent<br>application<br>intensity (2nd lag) | 28145        | 0.030 | 0.070        | 0      | 0.510 |
|                          | dt2      | Data technology<br>strength (2nd lag)             | 28145        | 0.030 | 0.070        | 0      | 0.480 |
|                          | lninfra  | Infrastructure                                    | 28145        | 5.010 | 4.280        | 0.930  | 8.940 |

**Table 1: Variable Descriptive Statistics** 

Source: Authors' compilation

Note: To mitigate the influence of extreme values, variables were winsorized at the 1% level.

The descriptive statistical characteristics of the above variables are summarized in Table 1. The instrumental variables (data1iv, data2iv), dummy variables (dt1, dt2) and IT infrastructure (lninfra) variables used in the subsequent instrumental variable regression, treatment effect regression and mechanism test are also listed here.

# Model Setting

This article first examines the relationship between data patent intensity as well as the market value performance of listed companies and establishes the following formula:

 $MV_{it} = \alpha_0 + \alpha_1 Patent_{it} + \sum_{j}^{n} = 2 \alpha_j Control^{j}_{it} + Year_t + Province_p + Industry_q + \varepsilon_{it}$ (1)

Among them, MV it represents the market value performance of enterprise i in year t and Intobin it is used as the explained variable in the regression analysis. Patent it represents the data patent strength of enterprise i in year t and is replaced by two core explanatory variables, data1 it and data2 it, in the regression analysis  $.^{j}$ it, Yeart, Province p, Industry q are other control variables, year dummy variables that affect the market value performance of enterprises, respectively.  $\epsilon_{it}$  is the error term.  $\alpha_{1}$  and  $\alpha_{j}$  are parameters to be estimated.  $\alpha_{1}$  is the parameter of interest in this paper, which indicates the direction and degree of influence of enterprises.

The following formula is established for the relationship between data patent strength and corporate financial performance:

 $FP_{it} = \beta_0 + \beta_1 Patent_{it} + \sum_{i}^{n} = 2 \beta_i Control^{j}_{it} + Year_t + Province_p + Industry_q + \varepsilon_{it}$ (2)

Among them, FP it represents the financial performance of enterprise i in year t. In the regression analysis, Inprofit it is used as the main explained variable, which is replaced by growth it and ROA it in the robustness test . Patent it represents the patent strength of enterprise i in year t. The specific setting is the same as formula (1). Add other control variables that affect the financial performance of enterprises.<sup>j</sup><sub>it</sub>, the setting of year, province and industry dummy variables is the same as in formula (1).  $\beta_1$  is the parameter of interest in this paper, which indicates the direction and degree of the impact of data patent intensity on corporate financial performance.

In view of the impact mechanism of data patent intensity on corporate profits, we add the moderating variable and the interaction term between the moderating variable and the core explanatory variable to equation (2) to establish the following formula:

| FP it = | β0+                     | $\beta_1$ Patent it + | $\beta_2$ Moderator it + | $\beta$ 3 Patent it × | Moderator it + | $\sum_{i}^{n} =$ |
|---------|-------------------------|-----------------------|--------------------------|-----------------------|----------------|------------------|
| 4 β; Co | ntrol <sup>j</sup> it + | Yeart+Provincer       | +Industry q +ε it        |                       | (3)            |                  |

The moderator variables that this paper focuses on include the company's own R&D personnel investment and R&D capital investment level, the degree of government subsidies received by the company and the level of IT infrastructure development. Therefore, on the basis of keeping other settings in equation (2) unchanged, the moderator variable Moderator <sub>it</sub> is replaced with R&D personnel investment and R&D capital investment, government subsidies and IT infrastructure variables. The regression coefficient  $\beta_3$  is used to analyze and determine the impact mechanism of data patent intensity on corporate profits.

| Variable   | Model 1                                  | Model 2      | Model 3   | Model 4              | Model 5   | Model 6   |
|--|--|--------------|-----------|----------------------|-----------|-----------|
|  | Intobit                                  | Intobit      | Intobit   | Intobit              | Intobit   | Intobit   |
| datal  | 0.0257***                                |              | 0.0177*** | 0.0185***            | 0.0158*** | 0.0147*** |
| Construction of the second sec | (5.62)                                   | free and the | (5.16)    | (4.54)               | (4.35)    | (3.38)    |
| data2  |  | 0.0284***    |           |                      |           |           |
|  | 8  | (5.38)       | -         |                      | ÷         | C         |
| Lnprofit   | -<br>0.0277***                           | - 0.0279***  | -0.0206** | -0.0211**            |           |           |
|  | (-3.72)                                  | (-3.76)      | (-2.29)   | (-2.34)              |           | 0         |
| ROA  | 3.196***                                 | 3.206***     | 2.613***  | 2.623***             |           |           |
| 1000   | (16.22)                                  | (16.25)      | (8.92)    | (8.95)               | 1         | 8         |
| Size   | -0.142***                                | -0.148***    | -0.151*** |                      |           |           |
|  | (-1.94)                                  | (-1.98)      | (-1.99)   | 1000 000 000 000 000 |           | 6         |
| Firmage  | 0.0745***                                | 0.0734***    | 0.0363**  | 0.0344**             |           |           |
|  | (5.89)                                   | (5.78)       | (2.08)    | (2.08)               | ÷         | 9         |
| SOE  | 0.0327***                                | 0.0334***    | 0.0337*** | 0.0326**             |           | 1         |
|  | (2.82)                                   | (2.86)       | (2.46)    | (2.51)               |           |           |
| Lev  | 0.129**                                  | 0.129**      | -0.0805** | -0.0791**            |           | 2         |
| and the second   | (4.35)                                   | (4.36)       | (-2.63)   | (-2.68)              | -         |           |
| Cashflow   | 0.336***                                 | 0.333***     | 0.329***  | 0.324***             |           |           |
|  | (7.34)                                   | (7.33)       | (7.29)    | (7.24)               |           |           |
| topl   | -0.404+++                                | -0.403***    | -0.328+++ |                      |           | 2         |
| 10.0 <u>0</u> .00  | (-9.86)                                  | (-9.86)      | (-6.25)   |                      |           |           |
| Balance  | -  | -            | -         | -                    |           | 2         |
|  | 0.0789***                                | 0.0786***    | 0.0613*** | 0.0654***            |           |           |
|  | (-8.68)                                  | (-8.65)      | (-6.16)   | (-5.33)              |           | -         |
| Indep  | 0.264+++                                 | 0.265***     | 0.241**   | 2                    |           | 2         |
|  | (3.88)                                   | (3.87)       | (2.46)    |                      |           |           |
| Lardeps  |  |              |           |                      | 0.0034    | -         |
|  | -  |              |           |                      | (0.63)    | C.        |
| Lnrdspd  |  |              |           |                      |           | 0.0046    |
| CONCERCIPTION  | 1  | 2            |           |                      | 1         | (0.71)    |
| Lngovsub   |  |              |           |                      |           | -0.0022   |
|  | () () () () () () () () () () () () () ( |              | 1         |                      |           | (-1.01)   |
| Observations   | 27312                                    | 27312        | 24759     | 24759                | 12003     | 12003     |
| Adjusted<br>R^2  | 0.218                                    | 0.218        | 0.505     | 0.505                | 0.501     | 0.498     |
| Year fixed<br>effects  | Yes                                      | Yes          | Yes       | Yes                  | Yes       | Yes       |
| Industry<br>fixed effects  | Yes                                      | Yes          | Yes       | Yes                  | Yes       | Yes       |

Table 2: Regression Results of Data Technology Capability and Enterprise Value

Source: Authors' compilation

Note: Values in parentheses are t-values. 2. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively. 3. Regression conducted using Stata software with reghfe command, results may vary.

# Analysis of the Impact of Enterprise Data Technology Capabilities on Market Value and Profits

This section uses panel data of 3,849 companies from 2009 to 2023 as the initial sample, analyzes and tests the impact of data technology capabilities on the market value and profits of listed companies and conducts robustness tests as well as endogeneity treatment on the benchmark regression results.

#### Benchmark Regression of Data Technology Capabilities and Corporate Performance

In view of the correlation between data technology capabilities and corporate market value, this paper uses a multidimensional fixed effect model for regression according to formula (1), controls the fixed effects of year, province and industry, and uses robust standard errors at the corporate level. A total of 6 submodels are constructed and the relevant results are summarized in Table 2. Model 1 and Model 2 use the data patent application intensity and data patent authorization intensity for univariate regression respectively. Models 3 to 6 add different control variables for regression. Among them, the variables such as R&D personnel investment, R&D capital investment and government subsidies used in Models 5 and 6 are not included in the subsequent related regression models because they have many missing values and do not bring about an increase in R2. Data patent intensity is significantly positive in all 6 sub-models, indicating that there is a significant and robust positive correlation between data patent intensity and corporate market value. Under the empirical model setting of this paper, keeping other conditions unchanged, the data technology capabilities of enterprises can have a significant effect on improving their market value.

In view of the correlation between data technology capabilities and corporate profits, six sub-models were constructed based on formula (2) for regression and year, province, industry fixed effects and enterprise-level clustering robust standard errors were also used. The relevant results are summarized in Table 3. The regression coefficients of data patent intensity in the six models are all significantly negative, indicating that there is a significant negative correlation between data technology capabilities and corporate profits. Therefore, under the setting of the empirical model in this paper, corporate data technology capabilities do not have a significant profitenhancing effect, that is, the production and operation activities and investments carried out by enterprises around data are difficult to achieve stable financial returns.

| Variable  | Model 1                   | Model 2                   | Model 3                   | Model 4                   | Model 5               | Model 6               |
|---|---------------------------|---------------------------|---------------------------|---------------------------|-----------------------|-----------------------|
|   | Lnprofit                  | Lnprofit                  | Inprofit                  | Inprofit                  | Inprofit              | Inprofit              |
| datal   | -<br>0.0672***<br>(-4.18) |                           | -<br>0.0397***<br>(-2.88) | -<br>0.0520***<br>(-3.33) | -0.137***<br>(-13.82) | -0.153***<br>(-13.41) |
| data2   |                           | -<br>0.0881***<br>(-4.85) |                           |                           |                       | <u>.</u>              |
| Firmage   | S S                       |                           | -0.0331<br>(-0.58)        | -0.0322                   | 0.202***<br>(3.66)    | 0.215*** (3.88)       |
| SOE   |                           |                           | 0.413***                  | 0.412*** (7.89)           | 0.155*** (3.19)       | 0.156***              |
| Lev   |                           |                           | 1.484***<br>(13.88)       | 1.481***<br>(13.84)       | 0.154<br>(1.45)       | 0.151<br>(1.42)       |
| Cashflow  |                           |                           | 5.167***                  | 5.164*** (23.99)          | 4.863*** (18.97)      | 4.877***              |
| topl  |                           |                           | 2.878***<br>(15.98)       | 2.874***<br>(15.94)       | 1.909*** (11.32)      | 1.902*** (11.28)      |
| Balance   |                           |                           | 0.514***<br>(13.02)       | 0.512***<br>(13.01)       | 0.288*** (8.05)       | 0.288***              |
| Indep   |                           |                           | -0.0898<br>(-0.28)        | -0.0896                   | -0.404 (-1.49)        | -0.412<br>(-1.51)     |
| Lnrdeps   |                           |                           |                           |                           | 0.198***              | 0.193***              |
| Lnrdspd   |                           |                           |                           |                           | 0.349***              | 0.349***              |
| Lngovsub  |                           |                           |                           |                           | 0.0669***             | 0.0672***             |
| Observations                                    | 25390                     | 25390                     | 25359                     | 25359                     | 12278                 | 12278                 |
| Adjusted R2                                     | 0.165                     | 0.165                     | 0.303                     | 0.304                     | 0.479                 | 0.477                 |
| Year,<br>Province,<br>Industry<br>Fixed Effects | Controlled                | Controlled                | Controlled                | Controlled                | Controlled            | Controlled            |
| Clustering<br>robust<br>standard<br>error       | Yes                       | Yes                       | Yes                       | Yes                       | Yes                   | Yes                   |

Table 3: Regression Results of Data Technology

**Capability and Enterprise Profit** 

#### Source: Authors' compilation

#### Robustness Test and Endogeneity Treatment

The study examines the impact of data technology capabilities on the market value and profits of listed companies. The results show that data patent intensity has a significant effect on the enterprise's market value, but negatively impacts its profits. The study also uses the annual growth rate of corporate operating income and the net profit margin of total assets as alternative indicators of corporate profits. The results are consistent with the benchmark regression results, indicating that data technology capabilities have not yet improved the financial benefits of listed companies. The study also uses the share shift method to construct Bartik variables for instrumental variable regression, revealing that data patent intensity enhances the market value, but negatively impacts profits. The results support the theoretical hypothesis that there are significant differences in the effects of enterprise data technology capabilities on market value and profits. However, if enterprises cannot convert these improvements into actual profit gains, it may negatively impact long-term market expectations and hinder technological innovation as well as development. Further research is needed to explore feasible paths for companies to achieve profit gains through data technology capabilities.

# Analysis of the Industry-Heterogeneous Impact and Mechanism of Enterprise Data Technology Capabilities on Market Value and Profits

This study examines the impact of data technology capabilities on the market value and profits of listed companies. It selects three sub-samples: Industrial enterprises, financial and wholesale and retail enterprises as well as professional service enterprises. Data patents are mainly concentrated in manufacturing, information transmission, software and information technology services. The study focuses on the industrial enterprise subsample, which includes manufacturing, construction, mining, electricity, heat, gas, water production and supply industries. The financial and wholesale and retail enterprises subsample analyzes the impact of data resources on corporate performance. The study concludes that data technology capabilities can enhance corporate value and empower client enterprises.

# Analysis of Regression Results by Industry

The study examines the impact of data patent intensity on the market value and profits of companies in three industries. The results show that the industries with the highest number of data patents and data development as well as utilization have a significant positive impact on the market value of listed companies. Financial, wholesale and retail enterprises have a greater impact on market value due to their focus on financial credit and precision marketing, primarily based on personal data analysis.

However, there is a significant negative correlation between data patent intensity and profits for industrial enterprises, as they face practical difficulties such as unclear application scenarios and complex production as well as manufacturing processes. In contrast, professional service enterprises show a positive impact trend, with service output based on their data technology capabilities potentially bringing profit increases. As shown in table 4, these results provide inspiration for further mechanism analysis and the identification of enterprise sub-samples that can achieve profit increases through data technology capabilities and related service outputs.

## Table 4: Regression Results of Data Technology Capabilities on Corporate Value and Profitability by Industry

| Variable                                     | Industrial I         | Enterprises           |                      |                       | Professiona<br>Enterprises |                       |  |
|--|----------------------|-----------------------|----------------------|-----------------------|----------------------------|-----------------------|--|
|  | Model 1<br>(Intobin) | Model 2<br>(Lnprofit) | Model 3<br>(Intobin) | Model 4<br>(Lnprofit) | Model 5<br>(Intobin)       | Model 6<br>(Lnprofit) |  |
| data2  | 0.0173*** (6.45)     | -0.0207***<br>(-3.24) | 0.198*** (2.98)      | 0.0788(0.48)          | 0.0205***<br>(4.43)        | 0.00405 (0.45)        |  |
| Observations                                 | 17075                | 17447                 | 773                  | 787                   | 2033                       | 2112                  |  |
| Adjusted R <sup>2</sup>                      | 0.441                | 0.658                 | 0.662                | 0.849                 | 0.487                      | 0.653                 |  |
| Control<br>Variables                         | Controlled           | Controlled            | Controlled           | Controlled            | Controlled                 | Controlled            |  |
| Year, Province,<br>Industry Fixed<br>Effects | Controlled           | Controlled            | Controlled           | Controlled            | Controlled                 | Controlled            |  |
| Clustered<br>Standard<br>Errors              | Yes                  | Yes                   | Yes                  | Yes                   | Yes                        | Yes                   |  |

#### Source: Authors' compilation

Note: The regression coefficients of data1 and control variables are omitted for brevity.

Industrial internet is a new form of digital economy that focuses on providing products and services for industrial enterprises through data collection, aggregation, analysis and application. This study aims to analyze the impact and mechanism of data patent intensity on the performance of industrial internet supplier companies. The research found that professional service companies that focus more on the output of technical products and services have a positive regression coefficient of data patent intensity on corporate profits. The paper also found that industrial imupntemet supplier companies can achieve a common increase in market value and profits through the external output of data technology capabilities. This is different from other industries because these companies can transform data into products and services for external output, resolving the contradiction between market value returns and financial benefits.

The research also analyzed the correlation between data patent intensity and corporate profits by adding supporting inputs/conditions that form a complementary relationship with data technology capabilities as moderating variables in the regression model. As shown in Table 5, four moderating variables were selected: R&D personnel investment, R&D capital investment, government subsidies and IT infrastructure of industrial internet supplier companies. The newly added IT infrastructure variable selected the cumulative value of the number of 4G and 5G base stations in the city where the listed companies are located from 2014 to 2023.

| Variable   | Model 1<br>(Intobin) | Model 2<br>(Intobin) | Model 3<br>(Intobin) | Model 4<br>(Intobin) | Model 5<br>(Lnprofit) | Model 6<br>(Lnprofit) | Model 7<br>(Lnprofit) | Model 8<br>(Lnprofit) |
|--|----------------------|----------------------|----------------------|----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| datal  | 0.0196** (2.56)      |                      |                      |                      | 0.0827***<br>(5.06)   |                       |                       |                       |
| data2  |                      | 0.0168* (1.97)       |                      |                      |                       | 0.0819*** (4.25)      |                       |                       |
| L. datal   |                      |                      | 0.0218*** (2.72)     |                      |                       |                       | 0.0856*** (4.64)      |                       |
| L. data2   |                      |                      |                      | 0.0189** (2.09)      |                       |                       |                       | 0.0947*** (4.31)      |
| Observati<br>ons                                   | 737                  | 737                  | 622                  | 622                  | 766                   | 766                   | 648                   | 648                   |
| Adjusted<br>R <sup>2</sup>                         | 0.576                | 0.574                | 0.618                | 0.616                | 0.752                 | 0.749                 | 0.749                 | 0.749                 |
| Control<br>Variables                               | Controlled           | Controlled           | Controlled           | Controlled           | Controlled            | Controlled            | Controlled            | Controlled            |
| Year,<br>Province,<br>Industry<br>Fixed<br>Effects | Controlled           | Controlled           | Controlled           | Controlled           | Controlled            | Controlled            | Controlled            | Controlled            |
| Cluster<br>Robust<br>Standard<br>Errors            | Yes                  | Yes                  | Yes                  | Yes                  | Yes                   | Yes                   | Yes                   | Yes                   |

## Table 5: Regression Results of Data Technology Capability on Firm Value and Profitability for Industrial Internet Supply Firms

#### Source: Authors' compilation

Note: The regression coefficients of control variables and other variables are not fully shown, but are reserved for reference.

The study reveals that investment in R&D and innovation can improve corporate profits by enhancing organizational management, human capital and business processes. Government subsidies can also provide financial support for enterprises with data technology capabilities, enhancing their profit-enhancing effect. The USA government has prioritized digital transformation in traditional industries, introducing policies and subsidies for industrial internet construction and "5G+Industrial Internet" technology transformation projects. These policies can guide digital development and provide financial support for innovation-driven enterprises. Additionally, IT infrastructure, particularly 4G and 5G mobile communication technologies can significantly impact data development and utilization, data technology capabilities and economic output as seen in Table 6. High IT infrastructure levels are more likely to increase corporate profits for industrial internet supplier companies.

How Big Data Patents Affect Enterprise Data Technology's Impact on Market Value and Profitability Page |30| Emerging Markets Journal Table 6: Regression Results of Data Technology Capability on Firm Profitability - Mechanism Test

| Variable                                     | Model 1 (R&D<br>Staff Input)          | Model 2 (R&D<br>Capital Input) | Model 3<br>(Government<br>Subsidies) | Model 4 (IT<br>Infrastructure) |  |
|--|---------------------------------------|--------------------------------|--------------------------------------|--------------------------------|--|
|  | Lnprofit                              | Inprofit                       | Lnprofit                             | Inprofit                       |  |
| datal  | 0.0718*** (2.94)                      | 0.0477*** (2.89)               | 0.0518*** (2.67)                     | 0.0847*** (3.88)               |  |
| Lnrdps                                       | 0.201*** (2.75)                       |                                |                                      |                                |  |
| c. datal × c. Lnrdps                         | 0.0305* (1.67)                        |                                |                                      |                                |  |
| Lnrdspd                                      |                                       | 0.376*** (6.82)                |                                      |                                |  |
| c. datal × c.<br>Lnrdspd                     |                                       | 0.0285** (2.54)                |                                      |                                |  |
| Lngovsub                                     |                                       |                                | 0.0592*** (2.89)                     |                                |  |
| c. datal × c.<br>Lngovsub                    |                                       |                                | 0.0294*** (3.22)                     |                                |  |
| Lninfra                                      |                                       |                                |                                      | 0.0869 (1.15)                  |  |
| c. datal × c. Lninfra                        | · · · · · · · · · · · · · · · · · · · |                                |                                      | 0.105*** (4.39)                |  |
| Observations                                 | 438                                   | 673                            | 766                                  | 440                            |  |
| Adjusted R <sup>2</sup>                      | 0.753                                 | 0.787                          | 0.762                                | 0.716                          |  |
| Control Variables                            | Controlled                            | Controlled                     | Controlled                           | Controlled                     |  |
| Year, Province,<br>Industry Fixed<br>Effects | Controlled                            | Controlled                     | Controlled                           | Controlled                     |  |
| Cluster Robust<br>Standard Errors            | Yes                                   | Yes                            | Yes                                  | Yes                            |  |

Source: Authors' compilation

Note: The regression coefficients of data2 (data patent authorization intensity), control variables, and other variables are not fully shown, but are reserved for reference.

Table 6 shows the impact mechanism of data technology capabilities on corporate profitability and examines the moderating effects of factors such as R&D personnel investment, R&D funding investment, government subsidies and IT infrastructure through different models. The results show that in all four models, data technology capabilities (data1) have a significant positive impact on corporate profitability (Lnprofit), and the coefficient is highly statistically significant. Specifically, the investment in R&D personnel and R&D funding has enhanced the contribution of data technology capabilities to corporate profits, while government subsidies and improvements in IT infrastructure have also significantly promoted the effect of companies using data technology capabilities to improve profitability. This shows that by increasing complementary inputs, companies can better convert data technology capabilities into actual profit growth.

# V. Discussion and Limitations

The study uses big data patent statistics related to data collection, analysis and application to reveal the significant role of enterprise data technology capabilities in improving market value. Especially in the financial and wholesale and retail industries, the enhancement of enterprise data technology capabilities has effectively enhanced the confidence of market investors, thereby promoting a significant increase in market value. This phenomenon shows that in the context of the digital economy, data have become an important part of the core competitiveness of enterprises, and its effective management as well as application can be directly reflected in the market valuation of enterprises.

Although enterprise data technology capabilities have a positive impact on market value, the study also points out that most companies face many limitations in converting data technology capabilities into actual profits. Especially in industrial enterprises, complex production processes and uncertain application scenarios make it difficult to directly reflect the economic benefits of data technology capabilities and even have a negative impact on profits in some cases. This reminds us that while improving data technology capabilities, companies also need to pay attention to its effective application path in actual business.

When facing the same challenges, industrial internet suppliers have successfully achieved a double increase in market value and profits by increasing complementary investments in R&D, capital, government subsidies and IT infrastructure. This successful experience provides important inspiration for the business community. In the process of applying data technology capabilities, companies should focus on building comprehensive technical support and application scenarios, and make up for the shortcomings of technology application through multi-faceted investments, thereby maximizing the economic benefits of data resources. In addition, the government and relevant industry associations should also play an active role in policy support and market environment optimization to create good external conditions for the application of enterprise data technology.

# VI. Conclusion and Recommendations

This paper examines the impact of enterprise data technology capabilities on the performance of listed companies in a specific country. It uses seven patent statistics, including cloud computing, big data, machine learning, deep learning, knowledge graphs, computer vision and natural language processing to construct a data patent intensity variable as a measurement indicator of these capabilities. The study matches financial data from NYSE U.S. 100 Index top companies and conducts an empirical analysis on the impact of these capabilities on market value and profits. The results show that data technology capabilities help increase the market value of listed companies, particularly for financial, wholesale, and retail companies. The application and holding of big data patents can signal a company's high level of data resource accumulation, strong data technology capabilities and good digital development direction. Financial, wholesale and retail companies mainly collect, analyze and apply personal data, which enhance investors' confidence in the market and have a more obvious market value improvement effect.

However, most companies struggle to convert the potential value of data resources into actual profits. Regression analysis shows a significant negative correlation between data patent intensity and corporate profits due to imperfect technical complementarity conditions and complex production business processes. Industrial internet supplier companies can transform data technology capabilities into profit means, with data patent intensity positively impacting market value and profits in multiple models. To promote data development and utilization, policy recommendations include cultivating data technology capabilities, increasing complementary investment and balancing short-term benefits with longterm development. Companies should clarify the key production factor status of data and its long-term value creation potential and have correct expectations for the development stage and initial returns of new technologies, models and formats. This paper suggests several strategies to enhance the economic benefits of data elements and

data technology capabilities. It suggests that enterprises should actively explore data application scenarios, develop data products and services and transform technical capabilities into business models and profit means. This will resolve constraints and difficulties faced by enterprises in data element strategic planning and investment decisions, enhancing the financial investment market's confidence in the big data industry.

In order to effectively promote the development and application of enterprise data technology, policymakers should focus on the following aspects: First, strengthen the construction of data factor market mechanism, promote the effective circulation and transaction of data resources. Second, increase policy support and financial subsidies for data technology research and development and application, encourage enterprises to increase R&D investment and enhance data technology innovation capabilities. In addition, data infrastructure construction should be strengthened, such as 5G networks, data centers, etc. to provide solid support for the application of enterprise data technology. Through these policy measures, a good external environment can be created for enterprises to promote the continuous improvement of their data technology capabilities and the steady growth of market value.

The paper also suggests accelerating the cultivation of specialized data intermediary service agencies to tap into the potential value of data elements in traditional industries. By providing value-added services like data collection, integration, processing and analysis, these services can reduce capital and technical thresholds, accelerate data resource development and fully realize the value creation potential of data elements in traditional industries. Fourth, the paper recommends accelerating the construction of data factor market mechanisms and supporting facilities to provide a high-quality external environment for data trading, circulation, development and utilization. It suggests that government departments and industry associations should strengthen policy guidance and support for data holding as well as using enterprises, enhance the awareness and willingness of micro-subjects to participate in data factor trading, circulation, development and utilization, and strengthen digital infrastructure such as 5G, data centers and artificial intelligence.

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