Research on Measuring the Value of Enterprise Data Assets Based on an Improved Excess Return Method Using XGBoost

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Abstract. In the context of the digital transformation of industries, data assets have become an important production factor in the development of the times. However, the measurement of their value is still in its infancy, and traditional valuation methods cannot assess their true worth. Based on the income approach, this paper improves the excess earnings method by proposing the use of the XGBoost model for prediction. The final value of a company's data assets is determined using the excess earnings rate, data asset share rate, and market value adjustment coefficient. The study also compares the value of companies with and without revenue contributions from data assets, thereby providing a reference for the valuation of data assets within the industry.

Keywords: Excess returns; data assets; XGBoost; Shapley;

1 Introduction

Against the backdrop of the ongoing global wave of technological revolution and industrial transformation, digital transformation has become the core driving force for high-quality development across all industries. As a key production factor in the era of the digital economy, the strategic value of data has been elevated to unprecedented heights. From the perspective of business operations, data assets not only optimize production processes and enhance decision-making efficiency but also give rise to new business models and revenue growth opportunities, gradually becoming a vital foundation for enterprises to build core competitiveness. With the gradual emergence of the data trading market and the continuous improvement of relevant policy frameworks, scientifically and accurately measuring the value of data assets has become a critical issue that urgently needs to be addressed across multiple scenarios, including enterprise asset management, market transaction pricing, investment and financing decisions, and the formulation of regulatory standards. However, the current field of data asset valuation is still in its exploratory and initial stages, which is clearly inconsistent with the importance of data assets. Data assets possess unique characteristics such as intangibility, uncertain returns, value synergy, and dynamic life cycles, which fundamentally differ from traditional tangible and intangible assets, making conventional valuation

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methods (such as the cost approach, market approach, and traditional income approach) difficult to adapt to their valuation needs. Specifically, the cost approach can only account for the formation costs of data assets and cannot reflect their potential future returns; the market approach is highly constrained in its application due to a lack of mature comparable transactions and uniform value benchmarks; although the traditional income approach focuses on future returns, it lacks precision in handling issues such as the nonlinear correlations and dynamic fluctuations of data asset returns, making it difficult to accurately isolate the excess returns of data assets and thus objectively assess their true value. While existing studies have recognized the limitations of traditional methods and attempted to improve data asset valuation, most research remains at the theoretical framework level, lacking practical methods that integrate advanced technologies such as machine learning, and thus cannot effectively support the practical application needs of enterprises.

Based on the aforementioned research gaps and practical challenges, this paper, grounded in the income approach, focuses on optimizing and improving the excess earnings method. It proposes the introduction of the XGBoost model for predictive analysis and, by integrating key indicators such as excess return rate, proportion of data assets, and market value adjustment coefficients, constructs a more scientific measurement system for enterprise data asset value. Meanwhile, by comparing the value differences between enterprises with and without contributions from data asset earnings, the effectiveness and applicability of this measurement system are further validated.

The conduct of this study holds significant theoretical and practical implications. On the theoretical level, it integrates machine learning techniques with traditional valuation methods, enriching the research perspectives and methodological framework for measuring the value of data assets, and provides new approaches to addressing the challenges of data asset valuation. On the practical level, the constructed valuation system can offer quantitative references for enterprises in pricing data assets, negotiating transactions, and managing assets, as well as support industry regulatory authorities in formulating relevant standards and regulating the data trading market.

2 Literature Review

In existing research, the multi-period excess return method is primarily employed for data asset valuation. Menggen Chen (2024)[1], after comparing the advantages and disadvantages of fundamental asset valuation methods, ultimately selected the multi-period excess return method as the valuation approach. Combined with a triple exponential smoothing model, this method ultimately determined the value of the target bank's data assets. Yaoyao Wang (2024) [2], enhanced the accuracy of this foundational valuation method by applying a grey prediction model based on the excess return approach. Using the differential method to reverse-engineer the discount rate for data assets, the author ultimately calculated the value of Haier Smart Home's data assets. Xiaoming Hu (2025)[3]built upon the excess return method, employing ARIMA models and trinomial tree models to optimize forecasting techniques, thereby determining the total value of corporate data assets. Rihui Ouyang(2024)[4], assessed commercial banks' off-balance-sheet data assets by integrating the analytic hierarchy process with the traditional multi-period excess return method, constructing an enhanced excess return approach to predict data asset value. Ye Cui (2022)[5]also applied this model to data asset valuation for logistics companies. Fenggang Li (2024) [6] combined the residual-corrected gray GM(1,1) model with the multi-start excess return method to estimate HSBC's data asset value. Yuyang Li [7] enhanced the FCFF model using XGBoost and applied it to corporate equity valuation, demonstrating its applicability in forecasting future operating revenues. Han Chang (2023) [8]and Wenzhang Sun (2023) [9]also employed the multi-period excess return method for data asset valuation. Hua Gao (2022) [10]analyzed from the perspective of data that data asset valuation requires scenario-based measurement. He proposed categorizing digital assets into transactional and non-transactional types based on application scenarios. For non-transactional scenarios, the Black-Scholes option pricing model offers more reasonable valuation, while for transactional scenarios, a comprehensive evaluation method combining AHP with the excess return approach yields better results. Xuejiao Xiao (2022) [11]employed the real options approach using least squares Monte Carlo simulation to determine the potential value of data assets. Applying this method to target enterprises, the study provides a solution for assessing the value of data assets in internet companies. B.Ai (2023)[12]categorized data asset valuation methods into monetary and non-monetary approaches. For monetary measurement, traditional valuation methods were applied throughout the entire lifecycle of data assets. Song (2016) [13]analyzed the lifecycle and valuation methods of data assets, concluding that data assets generate value for five years with diminishing returns over time. The study proposed a lifecycle estimation logic based on the half-life of data usage frequency and a DB asset valuation model. Zhang Wei (2025)[14]employed information entropy and TOPSIS methods to measure the weight of non-customized data assets, then utilized a neural network model to analyze and estimate the value of data assets.

Analysis of existing research indicates that most studies on data asset valuation rely on the excess return method. Improvements have been made to the calculation of the split ratio and excess returns within these models. Among these, the Analytic Hierarchy Process (AHP) is frequently employed to refine the split ratio model; however, this approach heavily depends on expert scoring, resulting in significant subjectivity. Regarding revenue forecasting, most studies rely on historical financial data, which is difficult to obtain and exhibits coarse granularity, failing to meet the data requirements of most predictive models. This paper proposes enhancing forecasting using the XGBoost model and employing the Shapley value method for contribution rate calculation, ultimately deriving the value of corporate data assets.

3 Theoretical Foundations

3.1 DCF

The DCF (Discounted Cash Flow) model, also known as the discounted cash flow model, calculates a company's intrinsic value by determining the present value of future cash flows using its financial data. Its formula is:

$$V = PV_1 + PV_2 = \sum_{t=1}^{n} \frac{FCF_t}{(1+r)^t} + \frac{FCF_n \times (1+g)}{(r-g)\times(1+r)^n} \tag{1}$$

Among them, $PV_1 = \sum_{t=1}^{n} \frac{FCF_t}{(1+r)^t}$ represents the summation of the discounted values of cash flows over the forecast period, where r denotes the discount rate, typically using the WACC value as the discount rate; $FCF_t$is the free cash flow for the t period, FCF_t= Net operating profit after tax+ Depreciation and amortization-Increase in working capital - Capital expenditures; $PV_2 = \frac{FCF_n \times (1+g)}{(r-g)\times(1+r)^n}$ represents the terminal value of the enterprise's assets over their perpetual life, and g denotes the asset growth rate.

3.2 XGBoost

XGBoost (extreme Gradient Boosting) is an advanced gradient boosting decision tree (GBDT) ensembles learning algorithm. Its core principle involves iteratively training a series of weak learners (typically decision trees), with each new tree dedicated to correcting the prediction residuals of its predecessor. The final output is obtained by performing a weighted sum of all trees' predictions. XGBoost's core advantages lie in its explicit incorporation of regularization terms (L1 and L2) within the objective function to control model complexity, effectively preventing overfitting. Its highly optimized parallel computing design significantly enhances training efficiency. The essence of its objective function (at iteration t) can be expressed as:

$$Obj^{(t)} \approx \sum_{i=1}^{n} [g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t) \tag{2}$$

where $g_i$and h_i denote the first order and second order gradients of the loss function, respectively, and $f_t(x_i)$ represents the t tree. $\Omega(f_t) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$ is a regularization term (where T denotes the number of leaf nodes, w represents the leaf weight, and γ and λ are hyperparameters).

3.3 Holt-Winters Model

The Holt-Winters model (also known as the cubic exponential smoothing method) is a classic time series forecasting technique designed to handle sequences containing trend and seasonal components. Its core principle involves dynamically weighting estimates of the time series' baseline level, incremental trend, and periodic fluctuations through three separate smoothing equations (level, trend, and seasonal), with weights controlled by three corresponding smoothing parameters (α, β, γ). Based on the relationship between seasonality and trend, the model is categorized into additive models (where the amplitude of seasonal fluctuations remains constant over time) and multiplicative models (where the amplitude of seasonal fluctuations increases as the trend level rises).

3.4 Shapley Value Method

The Shapley value is a concept originating from cooperative game theory, used to fairly measure the contribution allocation each participant (or feature) deserves within the total gains (or model prediction outputs) generated through cooperation. Its core principle is that a participant's contribution should be determined by the average of their marginal contribution across all possible cooperative alliance combinations. This method ensures the allocation satisfies the fairness axiom. Its formula is:

$$\phi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} (v(S \cup \{i\}) - v(S)) \tag{3}$$

Here, $\phi_i(v)$ denotes the Shapley value for participant i, where $|N|$ is the set of all participants, S is any coalition not containing s, and $v(S)$ is the payoff function for coalition S. Shapley values are typically employed to address interpretability issues in machine learning models.

4 Calculation Methodology

4. 1 Data Collection and Preparation

The data category comprises quarterly corporate financial data published from 2008 to 2024, along with daily closing prices during the target companies' listing periods from 2011 to 2024. Data sources originate from the Guotaian database, with model implementation relying on Python 3.9.

For missing values in the target company's financial data and daily closing prices, the corresponding periods were excluded. During the forecasting process, to address data discontinuities caused by holidays, the data (daily closing prices) were sequentially sorted.

4.2 Estimated Net Profit for the Forecast Period

Organize the target company's historical financial data and calculate its enterprise value using the DCF model. Compile the target company's daily closing prices during its listing period, using the average quarterly closing price as the quarterly market price per share. Multiply this by the current number of shares outstanding to derive the enterprise value. Conduct a comparative analysis of Enterprise Value 1 and Enterprise Value 2 to estimate the market value discrepancy, thereby determining the market value adjustment factor.

Input historical closing prices into the XGBoost model to perform multidimensional calculations on historical data, identifying key dimensions significantly influencing closing prices. Based on these selected dimensions, forecast closing prices for the prediction period. Multiply the forecast values by the market capitalization adjustment factor to obtain adjusted market capitalization forecasts. Calculate net profits for the prediction period using the DCF model.

4.3 Calculate the Relevant Adjustment Coefficients

Using the SARIMA model to forecast net profit based on historical financial data when no data assets have been constructed, the difference between the forecast value and the actual net profit is calculated to derive the company's excess return. The Holt-Winters (H-W) model is then applied to forecast the obtained excess return. For each quarter, the median value of the model's forecast for excess returns is taken to predict the excess return for that quarter.

The Shapley value method is employed to measure the allocation ratio of data assets and determine that excess returns comprise three components: data assets, capital, and labor. Capital consists of net fixed assets and construction in progress, while labor comprises employee wages and training expenses. Data assets, in turn, are composed of three elements: data asset wage inputs, data procurement costs, and data platform development investments.

4.4 Calculating the Value of Data Assets

Multiply the projected net profit by the excess return rate and the proportion of data assets to obtain the excess return attributable to data assets for each period within the forecast period. Discount the excess returns from each period to derive the projected value of the data assets. The technical roadmap for the entire experiment is shown in Figure 1.

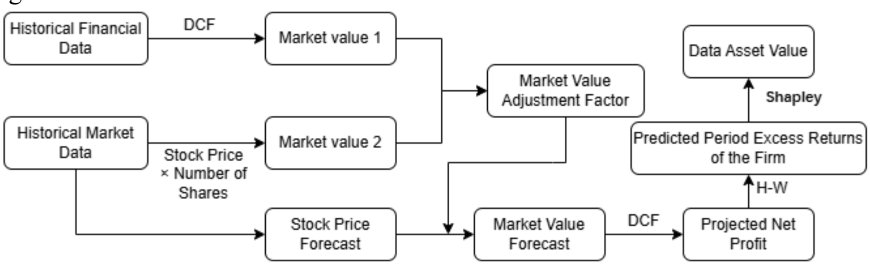

Fig. 1. Technical Roadmap

5 Case Applications

The case study company selected for this paper is BYD. First, financial data for BYD from 2008 to 2024 was collected. Using the DCF model, the company's free cash flow for the period 2015-2022 was calculated. This free cash flow was discounted to derive the company's market value 1. Daily closing prices during the target company's listing period were collected. The average closing price for each year was used as the quarterly stock price per share, multiplied by the current number of shares to derive Market Value 2. A comparative analysis between Market Value 1 and Market Value 2 was conducted to calculate the market value error, yielding the market value adjustment coefficient.

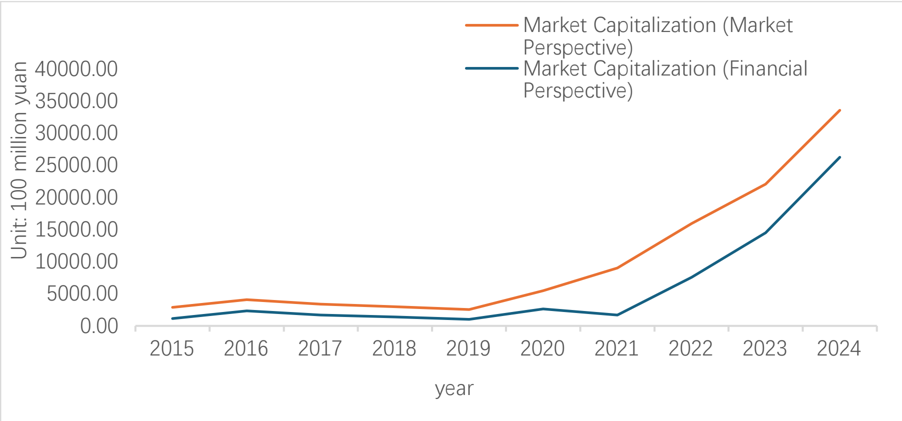

Fig. 2. Market Value Trend Chart

Figure 2 is a comparison chart of net profit trends. Given that stock prices are influenced by multiple factors and affected by non-productive market elements, market capitalization determined from a supply-demand perspective reflects changes in stock prices promptly when impacted, thereby altering market value. Conversely, market value calculated from a financial perspective is influenced by existing orders, partnerships, and the extent of media coverage, resulting in lagging estimates with relatively low volatility. Therefore, market capitalization errors exceeding 50% are excluded, and the average of the remaining errors is adopted as the market value adjustment coefficient, which is 6.78%.

Preliminary preparation was conducted on daily closing prices from 2011 to 2024. Prior to applying the XGBoost model to historical data, dimensionality reduction was performed. Multiple dimensions of the daily closing price time series data were tested for correlation, key features (TOP-K), prediction error (RMSE) increase ratio, and stability frequency. This process identified multiple dimensions influencing subsequent forecast data.

The 38 dimensions were screened based on correlation coefficients ≥0.9 and absolute increases in prediction error (RMSE) ≤8%, then ranked by feature importance. Ten dimensions were selected for subsequent model applications. Table 1 shows the 10 most influential factors selected.

Table 1. Dimensions Table of Influencing Factors

Influencing Factors	Relevance	Feature Importance	Percentage increase in RMSE	Stability Frequency
Price difference over the past 10 trading days	0.9534	0.9671	6%	1
Price changes over the past 10 trading days	0.9983	0.0070	0%	1
Week of the Year in Which the Transaction Date Falls	0.9991	0.0022	-3%	1
Moving median of closing prices over the past 60 trading days	0.9988	0.0019	-5%	1

Standard deviation of closing prices over the past 5 trading days	0.9977	0.0003	0%	1
Closing prices for the previous 10 trading days	0.9460	0.0003	5%	1
The moving median of closing prices over the past 20 trading days	0.9959	0.0003	-6%	1
Closing prices for the preceding 20 trading days	0.9708	0.0003	0%	1
Moving average of closing prices over the past 20 trading days	0.9948	0.0002	-2%	1
Moving median of closing prices over the past 90 trading days	0.9823	0.0002	2%	1

After completing the dimensionality filtering, the historical data is divided into training and testing sets. Considering that corporate data assets began impacting corporate earnings starting in 2021, the period from 2008 to 2023 is designated as the training set, while 2024 is allocated as the testing set. For the training set, we employed an XGBoost model to learn the correlation between net profit and various influencing factors. After training, we predicted the 2024 closing price, continuously adjusting model parameters until finalizing a maximum tree depth of 5 and a learning rate of 0.03. With these hyperparameters, the model converged rapidly and effectively. The chart below illustrates the trend of daily closing prices for the company, calculated using the XGBoost model.

Figure 3 is a stock price trend chart. The error validation on the test set produced the following metrics: Mean Absolute Error (MAE) = 5.40, Root Mean Square Error (RMSE) = 7.15, and Mean Absolute Percentage Error (MAPE) = 2.16%. These results indicate the model demonstrates strong predictive capability and is suitable for subsequent forecasting on the prediction set.

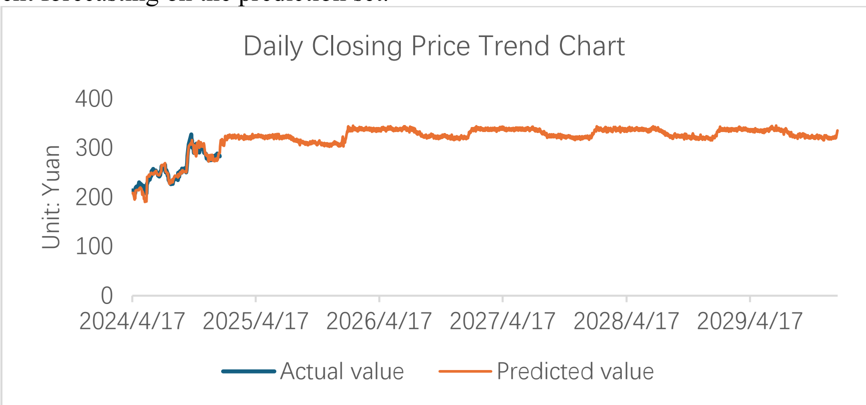

Fig. 3. Market Value Trend Chart

The final market capitalization forecast is obtained by multiplying the market cap adjustment factor by the market cap calculated as the product of the average annual stock price during the forecast period and the number of shares. This forecast is then combined with actual financial data to calculate net profit using the DCF model. The discount rate employed is the WACC discount factor, expressed mathematically as:

$$WACC = R_e \times \frac{E}{D+E} + R_d \times (1-t) \times \frac{D}{D+E} \tag{4}$$

As shown in Table 2, Re is calculated using the Capital Asset Pricing Model. The risk-free rate (rf) is based on the average yield of 5-year bonds from 2022 to 2024, i.e., 2.33%. The market rate of return (rm) is based on the average market yield from 2022 to 2024, i.e., 3.06%. The beta coefficient (β) uses the target company's beta coefficient at the end of 2024, i.e., 1.02. Rd is based on the average bond yield over the past five years. During the forecast period, the discount rate will be dynamically adjusted as the weighted average cost of capital (WACC) discount factor, reflecting changes in the debt-to-equity ratio.

Table 2. WACC Calculation Table

year	Re	Rd	E/(D+E)	D/(D+E)	WACC
2025	3.08%	2.33%	0.52	0.48	2.44%
2026	3.08%	2.33%	0.49	0.51	0.89%
2027	3.08%	2.33%	0.46	0.54	0.95%
2028	3.08%	2.33%	0.43	0.57	1.00%
2029	3.08%	2.33%	0.40	0.60	1.05%

Re is calculated using the Capital Asset Pricing Model, where rf represents the risk-free rate. The projected debt values for the forecast period are estimated using linear regression, with the regression equation defined as $y = 4\times10^{10}x + 8\times10^{10}$. The first quarter of 2021 constitutes the initial period (X=1), with subsequent periods following this pattern. The linear regression $R^2 = 0.9194$. The closer R^2 is to 1, the better the fit, indirectly indicating that the calculated results can serve as reliable projections.

Considering the target company's data asset investments commenced in 2021, the net profits from 2008 to 2020 were designated as the training set, while 2021 data served as the test set. These were input into the SARIMA model to forecast data for 2022–2024. The difference between the forecasted data and actual data was then calculated as the target company's excess returns.Figure 4 is a net profit trend chart. The difference between the two curves represents the excess return being sought. Through continuous adjustment of model parameters, the optimal model SARIMAX (0, 0, 2) × (0, 1, 1, 4) was obtained SARIMAX R^2 value of 0.671. This indicates that the model has to some extent learned the trends in historical data. The difference between the actual net profit and the forecasted net profit from 2021 to 2024 is treated as excess return, and the excess return rate is calculated as follows: 86.17%.

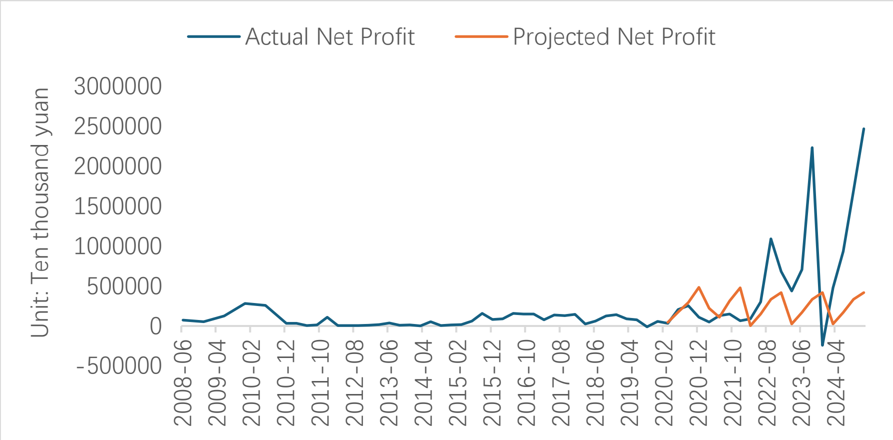

Fig. 4. Net Profit Trend

Based on the excess returns from 2022 to 2024, the H-W model was employed to forecast excess returns for the next five years (20 quarters). During iterative model parameter calibration, the objective function "Minimized Mean Squared Error (MSE)" was employed to optimize parameters using data from the calibration period (2021Q1-2024Q4). The optimal parameters obtained were: - Level smoothing coefficient $\alpha \approx 0.35$ - Trend smoothing coefficient $\beta \approx 0.1$ - Seasonal smoothing coefficient $\gamma \approx 0.45$ At this point, RMSE = 9.5%. Using the H-W model with these optimal parameters, we predict the excess returns. Table 3 is the forecast table of the target company's excess returns. By multiplying the target company's net profit during the forecast period by the excess return rate, the excess returns during the forecast period are obtained. Multiplying the obtained excess returns by the subsequent calculated data asset allocation rate will yield the data asset-generated excess returns during the forecast period.

Table 3. Excess Return Forecast Table

year	2025	2026	2027	2028	2029
Excess return	90%	89.5%	88%	87.5%	86.5%

The Shapley value method is employed to measure the share of data assets, with excess returns identified as comprising three components: data assets, capital, and labor. Among these, the data asset component can be indirectly obtained through analysis of third-party research reports. The 2022 White Paper on Digital Talent in the Intelligent Vehicle Industry states in its section on "Talent Demand Structure in the Intelligent Vehicle Industry" that "positions in data R&D, artificial intelligence algorithms, and intelligent driving account for 25% of the R&D team. Therefore, the wage investment for data assets is set at 25% of employee compensation within R&D expenses." Deloitte's 2024 Automotive Industry Data Asset Value Report indicates that mainstream automakers' data procurement costs range from 0.6% to 1.2% of operating revenue. In this case study, a 0.8% ratio is adopted to determine data procurement costs. Deloitte's 2024 Automotive Industry Software Value Report indicates that mainstream automakers allocate 25%-35% of their total software investment to data platform development. In this case, a 30% ratio is applied to determine the investment in data asset platform development. After calculation using the Shapley value method, the share ratio of data assets is determined to be: 34.86%. The capital share ratio is: 32.56%. The labor share ratio is: 32.58%. After discounting, the projected excess return share of data assets is derived, with the value of data assets amounting to RMB 12,885,821,605.00.

6 Conclusion

We are currently in the era of the digital economy, where data has become a key factor of production driving economic growth. Accurately assessing the value of data assets holds significant importance for both enterprises and society. Therefore, this paper aims to explore methods for evaluating the value of data assets and their applications. In applying data asset valuation methods, an improved approach is proposed to address the strengths and weaknesses of traditional methods, providing a reference for subsequent refinement. This improved method is applied to corporate data asset valuation to demonstrate the feasibility of the enhanced model.

A key challenge in measuring corporate data asset value lies in calculating the excess return sharing rate for data assets. This rate is derived from industry research reports in the market, which may not reflect the government's stance on data assets and could influence subsequent value calculations. Furthermore, the data asset sharing rate is calculated based on employee wages, procurement costs, and development investments, potentially leading to a mismatch between costs and benefits. Therefore, the government should introduce relevant policies and standards to strengthen guidance and support for corporate digital transformation. This includes empowering enterprises with funding, technology, and talent, while promoting improvements in data collection, storage, transmission, sharing, and analysis capabilities to achieve efficient management and utilization of data resources. Efforts should accelerate the establishment of data asset classification standards and the construction of a data asset accounting framework.

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