The Impact of Data Asset Recognition on Stock Price Synchronicity

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Abstract. Since the implementation of the data asset recognition policy, corporate data resources have gradually changed from off-balance-sheet descriptions into accounting information that can be recognized and reported. However, its capital market effects have not been fully examined. Using A-share listed firms from 2020 to 2025 as the sample, this paper applies a PSM-DID model to examine the effect of data asset recognition on stock price synchronicity. The empirical results show that data asset recognition significantly increases firms' stock price synchronicity. Stock turnover has a mediating effect in this relationship. Heterogeneity tests further show that the effect is significant mainly among firms with low institutional ownership and high analyst attention. This paper enriches the literature on the economic effects of data asset recognition and provides empirical evidence for improving data asset recognition rules and guiding investors to price firms more rationally.

Keywords: Data asset recognition, Stock price synchronicity, Capital market pricing, DID, Information environment.

1. Introduction

In the digital economy, data resources have been widely used in areas such as customer identification, product development, supply chain management, and risk control. They are becoming an important source of competitive advantage for firms. However, traditional financial reports mainly focus on tangible assets and common intangible assets. As a result, they often fail to reflect the economic value of data resources timely. To address this issue, the Ministry of Finance issued the Interim Provisions on Accounting Treatment for Enterprise Data Resources in 2023. Under this policy, qualified data resources can be recognized as intangible assets, inventories, or development costs.

Stock price synchronicity reflects the extent to which individual stock returns can be explained by common market and industry factors, and serves as an important indicator measuring the information structure of capital markets. Generally, when more firm-specific information is included in stock prices, stock price synchronicity is expected to decrease. Therefore, it is important to examine whether data asset recognition can provide firm-specific information and further affect stock price synchronicity. However, most existing studies focus on how data asset disclosure affects capital market pricing efficiency, stock price synchronicity, and stock price crash risk. Other studies examine the impact of the data asset recognition policy on firm value and stock market reactions. There is still little empirical evidence on whether data asset recognition itself affects stock price synchronicity.

Therefore, using A-share listed firms as the sample, this paper empirically examines whether data asset recognition affects stock price synchronicity. This paper has three main contributions. First, it provides a better understanding of the relationship between data asset recognition and stock price synchronicity. Existing studies mainly focus on data asset disclosure, data asset recognition policies, firm value, and stock market reactions. Research on stock price synchronicity usually focuses on general information disclosure and the information environment. However, few studies directly examine how data asset recognition affects stock price synchronicity; Second, this paper provides more evidence for the "noise view" of information disclosure. Prior studies offer the information view and the noise view on how information disclosure affects stock price synchronicity. The information view argues that better disclosure can reduce stock price synchronicity. However, this paper shows that data asset recognition supports the noise view; Third, this paper reveals that new accounting information may have a common signal effect in the early stage of policy implementation. It also provides useful evidence for regulators to improve the data asset recognition and disclosure system.

2. Literature Review

2.1. Studies on the Economic Effects of Data Asset Recognition

Existing studies usually discuss the economic effects of data asset recognition from two perspectives: data asset information disclosure and data asset recognition policy. Early studies mainly examined whether firms disclosed data asset information and what economic effects were caused by the level of disclosure. Later studies began to focus on the economic effects of the data asset recognition policy. Overall, however, there are still few studies that directly examine the economic effects of firms' actual data asset recognition behavior.

Most of the previous studies have been carried out from the perspective of data asset information disclosure. The measurement methods used are mainly annual report keywords, text analysis or disclosure index. However, the conclusions are not completely consistent. Some scholars, such as Li Shigang et al. (2025), Li Xiaoying et al. (2025), as well as Xu Haiwei and Liu Hua (2024), believed that data asset information disclosure can bring up information supply, reduce information asymmetry, and enhance investors ' ability to identify firm-specific information [1,2,3]. In this way, stock price synchronicity decreases. However, Li Meng et al. (2025) pointed out that in those markets with strong noise trading and investor follow-up behavior, data asset information disclosure may increase stock price synchronicity [4]. Behind this situation, it may reflect the enhancement of market common expectations, or the reduction of noise disturbance. Furthermore, Zhang Shushan et al. (2025) also found that data asset information disclosure can have an impact on the risk of stock price crash [5].

In the later period, with the implementation of the policy, some studies began to pay attention to the impact of data asset recognition policy. Zhao Zhigang (2024) mentioned that the value of data resources can be made explicit by entering the table, but in practice, problems such as data right confirmation, compliance governance, cost collection and value evaluation will still be encountered [6]. Huang Can et al. (2024) found that the data asset recognition policy can trigger positive expectations of investors and affect the market value of enterprises through financial statement effect and financing effect [7]. Wang Jiexuan and Gong Zihui (2024) took the policy as the object, and saw that A-share companies with a higher degree of digitization had positive cumulative excess returns, and the more opaque the information environment, the more obvious the stock price response, indicating that the policy can alleviate information asymmetry [8].

In general, the existing literature mostly focuses on data asset information disclosure and data asset recognition policies, and less on the economic consequences of actual data asset recognition.

2.2. Studies on the Influencing Factors of Stock Price Synchronicity

Stock price synchronicity reflects the extent to which individual stock price movements are explained by common market and industry factors. According to Roll (1988), the part of individual stock returns that cannot be explained by common market factors usually reflects firm-specific information [9]. In general, higher stock price synchronicity indicates a lower degree of firm-specific information being incorporated into stock prices. In emerging capital markets, low information transparency can increase stock price synchronicity and weaken the incorporation of firm-specific information into stock price [10,11].

There has been rich research on the factors affecting stock price synchronicity. Most studies use empirical models to examine the effects of different factors on stock price synchronicity. Among them, information disclosure is one of the most important research topics. Overall, information disclosure can affect how firm-specific information is incorporated into stock prices. However, its effect may vary depending on disclosure content, market environment, and investor behavior.

On the one hand, different types of information disclosure will affect stock price synchronicity. Ruan et al. (2024) found that ESG disclosure will increase stock price synchronicity [12]; Wei Ping and Zeng Gaofeng (2018) found that environmental information disclosure is positively correlated with stock price synchronicity by using A-share environmentally sensitive industries as samples [13]. In terms of financial information disclosure, Gelb and Zarowin (2002) found that the stock price of enterprises with high disclosure level can better reflect the future earnings information, indicating that high-quality financial disclosure helps to improve the information content of stock price [14]. However, there are two views for the impact of information disclosure on stock price synchronicity. The first is the "information view", which believes that the more adequate information disclosure, the easier it is for investors to identify company-specific information, and the stock price synchronicity will decline. Durnev et al. (2003) suggested that higher firm-specific return variation usually means that stock prices contain more firm-level information [15]. Haggard et al. (2008) found that voluntary disclosure can improve the information content of stock prices and reduce stock price synchronicity [16]. The second view is the "noise view", which suggests that more sufficient information disclosure may increase stock price synchronicity. Dasgupta et al. (2010) argued that higher transparency does not necessarily reduce stock price synchronicity. After more information is incorporated into prices in advance, future firm-specific information shocks may become weaker, so stock price synchronicity may rise instead [17].

On the other hand, the literature on information disclosure also clarifies how accounting information affects stock price synchronicity. Healy and Palepu (2001) believed that disclosure can alleviate information asymmetry and allow company-specific information to enter the stock price [18]. Lambert et al. (2007) pointed out that the quality of accounting information and disclosure will affect investors ' judgment of cash flow and risk, which in turn affects pricing [19]. Piotroski and Roulstone (2004) also found that analysts, institutional investors and insiders push information into stock prices in different ways. Analysts and institutional investors can both enhance the ability to interpret information and may also strengthen the dissemination of common information in the industry [20]. In summary, existing studies explain the effect of information disclosure on stock price synchronicity through two views: the information view and the noise view. However, under data asset recognition, recognized data assets combine accounting recognition, policy signaling, and digital economy concepts. If investors find it difficult to distinguish quality differences across firms, data asset recognition may be viewed as a common policy signal, thereby increasing stock price synchronicity. Therefore, its effect on stock price synchronicity has important theoretical value.

3. Theoretical Analysis and Research Hypotheses

According to the noise view, more sufficient information disclosure may lead to higher stock price synchronicity. Dasgupta et al. (2010) argued that higher transparency does not necessarily reduce stock price synchronicity. Once information is incorporated into prices in advance, later firm-specific information shocks may become weaker, so stock price synchronicity may increase instead [17].

Since data asset recognition is still in its early stage and has special features, it may bring noise to the market. Investors may not be able to accurately judge the real quality and future returns of data assets of different firms. On the one hand, data asset recognition among A-share listed firms is still in its early stage, and firms differ greatly in disclosure standards and disclosure depth [21]. On the other hand, data asset recognition is not a kind of general text disclosure. It turns data resources into observable information in financial statements. Although this process makes the value of data resources more visible, it still faces problems such as data ownership confirmation, compliance governance, cost collection, and value assessment [6]. These problems may influence investors' judgments about recognized amounts and future returns.

In summary, at the early stage of policy implementation, data asset recognition may mainly serve as a common signal rather than sufficient firm-specific information. Investors may regard it as a signal of the digital economy, data elements, or policy support, thus increasing common attention to related firms. Its mechanism can be summarized as follows: data asset recognition makes information harder for investors to understand and brings noise to the market. The noise and common attention then further increase stock price synchronicity. In addition, Li Meng et al. (2025) found through empirical analysis that data asset-related information may increase stock price synchronicity in markets with strong noise trading and herding behavior [4]. Therefore, this paper argues that data asset recognition may increase firms' stock price synchronicity in the short term. Based on the above analysis:

H1: Data asset recognition significantly increases firms' stock price synchronicity.

Furthermore, stock turnover may serve as an important transmission channel. A higher turnover rate usually means more active trading, and such trading may include transactions based on firm-specific information. In this case, firm information is more likely to be incorporated into stock prices through trading [22,23]. By contrast, lower stock turnover may weaken the incorporation of firm-specific information into stock prices. In the early stage of data asset recognition, investors may face uncertainty in judging the value of data assets [6]. This uncertainty may reduce trading activity and thereby increase stock price synchronicity. Therefore, the following hypothesis is further proposed:

H2: Data asset recognition increases firms' stock price synchronicity by reducing stock turnover.

The external information environment may influence how strongly data asset recognition affects stock price synchronicity. Institutional investors and analysts both play a role in the incorporation of information into stock prices, but their effects may work in different directions. Existing studies show that analysts, institutional investors, and insiders influence how market information, industry information, and firm-specific information are incorporated into stock prices in different ways, thereby affecting stock price synchronicity [20]. In emerging markets, higher analyst coverage may also increase stock price synchronicity, indicating that information intermediaries may strengthen the transmission of common information [24].

On the one hand, institutional investors tend to play a role in monitoring and value identification. When institutional ownership is high, the market is more likely to distinguish the real quality of data asset recognition, and the conceptualized interpretation of such information is relatively weaker [20]. By contrast, when institutional ownership is low, firms lack the supervision and explanation provided by professional investors. Ordinary investors are more likely to regard data asset recognition as a policy hotspot. Therefore, for firms with low institutional ownership, data asset recognition is more likely to be interpreted as a policy-related signal, and its effect on increasing stock price synchronicity may be stronger.

On the other hand, analyst attention mainly plays a role in information transmission. When analyst attention is high, data asset recognition information is more likely to be captured and spread by the market. This may strengthen investors' common expectations about the digital economy and data elements [25]. When analyst attention is low, such information spreads within a smaller range, and common market attention is relatively weaker. Based on the above analysis:

H3a: Data asset recognition has a stronger effect on increasing stock price synchronicity among firms with lower institutional ownership.

H3b: Data asset recognition has a stronger effect on increasing stock price synchronicity among firms with higher analyst attention.

4. Research Design

4.1. Sample Selection and Data Sources

Since the data asset recognition policy began to be implemented in 2024, this paper uses A-share listed firms from 2020 to 2025 as the research sample. The years 2020–2023 are defined as the pre-policy period, and 2024 and later years are defined as the post-policy period. To ensure the quality of the sample, this paper applies the following procedures. First, listed firms in the financial industry are excluded. Second, ST and *ST firms are removed. Third, observations with missing core variables are deleted. Finally, all continuous variables are winsorized at the 1% and 99% levels to reduce the impact of extreme values on the regression results. Furthermore, to reduce the possible sample selection bias between firms with and without data asset recognition, this paper uses firm characteristics in 2023 to conduct 1:1 nearest-neighbor matching based on a Logit-PSM model. The

DID regression is then performed using the matched sample. After matching, the final main regression sample includes 238 firms and 1,320 firm-year observations.

The main data used in this paper are obtained from the CSMAR database, and all data processing is conducted using Stata.

4.2. Model Design and Variable Definitions

To test the effect of data asset recognition on stock price synchronicity, this paper constructs the following DID model:

$$SYN_{i,t} = \alpha + \beta DID_{i,t} + \gamma Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{1}$$

In this model, SYN represents stock price synchronicity, DID is the treatment variable for data asset recognition, and Controls denotes a set of control variables. μ_i and λ_t represent firm fixed effects and year fixed effects, respectively, while $\varepsilon_{i,t}$ is the random error term. Clustered robust standard errors are adjusted at the firm level. If β is significantly positive, it means that data asset recognition significantly increases firms' stock price synchronicity. If β is significantly negative, it means that data asset recognition reduces firms' stock price synchronicity. Based on the research hypothesis, this paper expects β to be greater than zero.

4.2.1. Dependent Variable: Stock Price Synchronicity (SYN)

Referring to the studies on stock price synchronicity by Roll (1988), Morck et al. (2000), Durnev et al. (2003), and Jin and Myers (2006), this paper uses the stock price synchronicity indicator provided by the CSMAR database and calculated by the comprehensive market tradable-market-value average method as the main variable. To check the robustness of the results, this paper further uses SYN_alt as an alternative dependent variable. SYN_alt is a stock price synchronicity indicator from the CSMAR database and is calculated based on the comprehensive market total-market-value average method. A higher SYN means that individual stock prices are more likely to move together with common market or industry factors, indicating less firm-specific information in stock prices.

4.2.2. Core Explanatory Variable

The core explanatory variable is DID, which measures the effect of data asset recognition. First, this paper constructs Treat. If a firm has data asset recognition behavior during the sample period, Treat equals 1; otherwise, it equals 0. Then, this paper constructs Post. Since the data asset recognition policy was implemented in 2024, Post equals 1 for observations in 2024 and later years, and 0 otherwise. Finally, the core explanatory variable is defined as DID = Treat × Post.

4.2.3. Mediating Variable: Stock Turnover

Using daily stock trading data, this paper calculates each firm's annual average turnover rate and constructs lnTurnover as the natural logarithm of one plus this rate. A higher turnover rate means that the stock is traded more actively and has better liquidity, while a lower turnover rate means that trading activity declines.

4.2.4. Main Variable Definitions

To reduce omitted variable bias, this paper adds a set of control variables. The definitions of all variables used in this paper are presented in Table 1.

Table 1. Main Variable Definitions

Variable Type	Variable	Symbol	Definition
Dependent Variable	Stock Price Synchronicity	SYN	Provided by the CSMAR database.
		SYN_alt	Provided by the CSMAR database.
Explanatory Variables	Data Asset Recognition	DID	The interaction term between Treat and Post.
Mechanism Variable	Stock Turnover	lnTurnover	Ln(1+ the stock turnover rate).
Control Variables	Firm Size	Size	The natural logarithm of total assets.
	Leverage	Lev	Total liabilities divided by total assets.
	Profitability	ROA	Return on total assets.
	Growth	Growth	Growth rate of operating revenue.
	Tobin's Q	TobinQ	Market value/the replacement cost of its assets.
	Book-to-Market Ratio	BM	Book value/market value.
	Loss	Loss	Equals 1 if net profit is negative, and 0 otherwise.
	Firm Age	FirmAge	Ln(1+ the number of years since the firm was listed).
	Largest Ownership	Top1	The shareholding ratio of the largest shareholder.
	Board Size	Board	Ln(1+the number of board directors).
	Institutional Ownership	Institution	The shareholding ratio of institutional investors.
	Analyst Attention	Analyst	Ln (1+ the number of analyst reports).

5. Empirical Results

5.1. Baseline Regression Results

Column (1) of Table 2 presents the baseline regression results. The coefficient of DID is 0.0385 and is statistically significant at the 5% level. Therefore, Hypothesis H1 is supported.

Table 2. Baseline, Robustness, and Mechanism Test Results

	(1) SYN	(2) SYN_alt	(3) lnTurnover	(4) SYN
DID	0.0385**	0.0424**	-0.0033*	0.0312*
	(2.17)	(2.42)	(-1.76)	(1.73)
lnTurnover				-1.2632***
				(-3.49)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
_cons	-0.3593	-0.3595	0.1406*	-0.3504
	(-0.59)	(-0.59)	(1.75)	(-0.55)
Observations	1320	1320	1285	1285

Notes: ***, **, and * ,1%, 5%, and 10%. The values in parentheses are t-statistics. The same applies below.

5.2. Robustness Tests

5.2.1. Parallel Trend Test

To examine whether the parallel trend assumption of the DID model is satisfied, this study plots the dynamic effects before and after the recognition of data assets, as shown in Figure. 1.

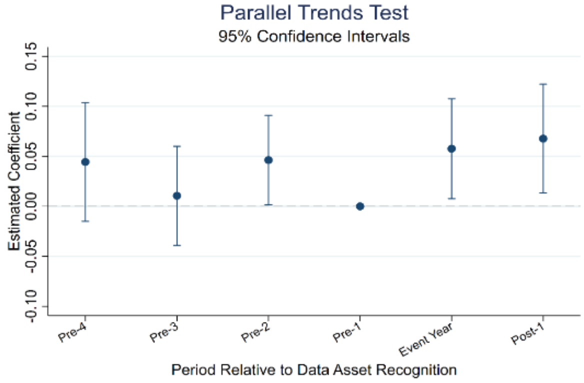

Figure 1. Parallel Trend Test

The parallel trend test shows that the coefficients for the periods before data asset recognition are generally not statistically significant. A joint significance test is also conducted for these pre-treatment coefficients, and the result is Prob > F = 0.1259. This means that the pre-treatment coefficients are not jointly significant. Therefore, the parallel trend assumption is generally satisfied.

5.2.2. Placebo Test

The placebo test further supports the reliability of the main findings. The paper randomly selected the same number of firms as in the actual treatment group to form a placebo treatment group and repeat the regression 500 times. The results are shown in Figure 2.

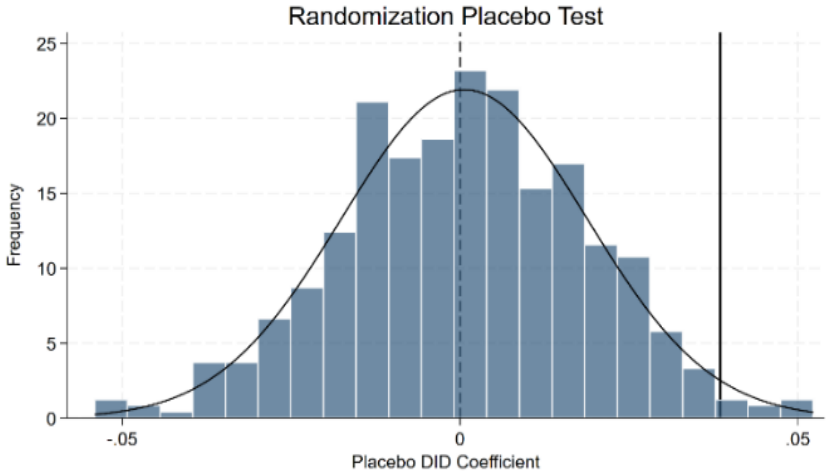

Figure 2. Placebo Test

The randomly generated DID coefficients are mainly distributed around zero, while the actual DID coefficient lies on the right side of this distribution. This result suggests that the positive effect of data asset recognition on stock price synchronicity is robust.

5.2.3. Alternative Measure of the Dependent Variable

To ensure that the results are not driven by a single measure of stock price synchronicity, this study uses the alternative measure, SYN_alt, and repeats the regression analysis.

As shown in Table 2, the coefficient of the key variable DID remains positive. This means that data asset recognition still increases firms' stock price synchronicity when an alternative measure is used. Therefore, the main finding is robust.

6. Mechanism Test and Further Analysis

6.1. Mediation Effect Test: The Stock Turnover Mechanism

Column (3) of Table 2 uses lnTurnover as the dependent variable to examine whether data asset recognition affects stock turnover. The results show that the coefficient of DID is −0.0033 and is statistically significant at the 10% level. Column (4) of Table 2 further includes lnTurnover in the regression model of stock price synchronicity. The coefficient of lnTurnover is −1.2632 and is statistically significant at the 1% level, while the coefficient of DID becomes smaller than that in the baseline regression. These results support the mediating role of stock turnover and Hypothesis H2.

6.2. Heterogeneity Analysis

6.2.1. Heterogeneity by Institutional Ownership

The sample is divided into a high institutional ownership group and a low institutional ownership group based on the median institutional ownership ratio. Separate regressions are then conducted for the two groups, and the results are reported in Table 3.

Table 3. Heterogeneity Analysis

	(1) Low Institutional Ownership	(2) High Institutional Ownership	(3) Low Analyst Attention	(4) High Analyst Attention
DID	0.0737***	0.0080	0.0071	0.0674***
	(3.08)	(0.31)	(0.28)	(2.68)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
_cons	0.0930	-0.9545	0.9805	-1.4650
	(0.13)	(-0.86)	(1.09)	(-1.64)
Observations	658	662	685	635

The results in Table 3 show that, for firms with low institutional ownership, the coefficient of DID is 0.0737 and is statistically significant at the 1% level. These results show that the positive effect of data asset recognition on stock price synchronicity mainly exists in firms with low institutional ownership. Therefore, Hypothesis H3a is supported.

6.2.2. Heterogeneity by Analyst Attention

The sample is divided into a high analyst attention group and a low analyst attention group based on the median level of analyst attention. The regression results are reported in Table 3.

The results in Table 3 show that, for firms with high analyst attention, the coefficient of DID is 0.0674 and is statistically significant at the 1% level. Therefore, Hypothesis H3b is supported.

7. Conclusions and Future Research

Using data from Chinese A-share listed firms from 2020 to 2025, this study applies the PSM-DID method and finds that data asset recognition significantly increases firms' stock price synchronicity. Further analysis indicates that a decline in stock turnover is one possible channel through which this effect occurs. The effect is more pronounced among firms with lower institutional ownership and greater analyst attention. The results of the parallel trend test, the alternative measure of the dependent variable, and the placebo test also support the main findings. Theoretically, this study shows that data asset recognition does not necessarily reduce stock price synchronicity immediately. Instead, it may increase stock price synchronicity by attracting common market attention and encouraging concept-driven interpretations. This finding provides support for the "noise view".

From a practical point of view, the regulatory authorities must further improve the disclosure requirements of data assets, so that the comparability and comprehensibility of information can be improved. Listed firms should clearly explain how data assets are developed, used, and translated into economic benefits. Investors can not only focus on whether the data assets are included in the table and the amount, but also need to combine the main business, profitability and data usage scenarios to analyze. In this way, data asset recognition can be better played out.

There is still room for further expansion in this paper. First of all, this paper does not distinguish different types of data asset projects. Subsequent research can examine separately what impact different entry items will have on stock price synchronicity, corporate value and investor response. Secondly, the implementation of the data asset entry system is not long after all, and what will be the long-term impact of it remains to be seen. Furthermore, this paper 's attention to the quality of corporate disclosure is not deep enough. Future research can also incorporate the quality of disclosure into the analysis while continuously tracking the long-term impact.

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