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Digital Disruption in Asset Pricing: Re-examining CAPM Assumptions in Platform Economies and Algorithmic Trading Era

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Abstract:

We examine the theoretical impact of digital technologies on the CAPM and trace the pathways through which these technologies reshape asset pricing mechanisms. Findings reveal that the rapid development of platform economies and algorithmic trading is challenging the three core assumptions of CAPM: market efficiency, investor rationality, and mean-variance preferences. Digital technologies have reconfigured asset pricing mechanisms by altering market microstructure, reshaping risk-return relationships, and introducing novel pricing logic channels. Empirical results indicate that digital transformation exerts a significant positive impact on firm value but a negative effect on short-term asset returns, revealing the limitations of traditional CAPM in explaining asset pricing in the digital era. This study offers a new theoretical perspective for understanding asset pricing patterns in the digital finance era, providing important implications for investment practice and financial regulation.

Keywords: Digital Technology; Platform Economy; Asset Pricing; CAPM

1. Introduction

The revolutionary development of digital technology is profoundly reshaping the operational paradigm of global financial markets, with platform economy and algorithmic trading serving as the two core driving forces. Relying on its unique bilateral market structure and significant positive network externalities, the platform economy has built a highly interconnected market ecosystem. This not only breaks through the business boundaries of traditional financial intermediaries, but also realizes the intelligent transformation of financial services through big data analysis and artificial intelligence technology. Take the leading fintech platform as an example. By integrating multidimensional heterogeneous data such as transaction behaviour data, social network data and real-time market data to build a dynamic risk assessment model, it has achieved precise pricing and personalized recommendation of financial products, significantly improving the efficiency of market allocation. Meanwhile, algorithmic trading systems have achieved intelligent and automated trading decisions by leveraging high-performance computing, machine learning algorithms, and low-latency communication technologies. Modern algorithmic trading systems

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can process massive market data on a millisecond time scale and execute complex trading strategies. Their trading scale and execution efficiency have comprehensively surpassed the traditional manual trading model, making them the main provider of market liquidity.

The Capital Asset Pricing Model (CAPM), which serves as the cornerstone of modern finance, is based on a series of strict assumptions for its theoretical validity, including the complete efficiency of the market, the complete rationality of investors, and frictionless transactions. However, in a market environment dominated by the platform economy, the decision-making process of investors is significantly disturbed by the interface design of the platform, the influence of social networks, and cognitive biases, which is obviously contrary to the rational investor assumption of CAPM. What is more worthy of attention is that although the decision-making logic of algorithmic trading systems has a formal "rational" feature, the prediction models trained based on historical data may imply systematic biases, and the homogenization of algorithms may trigger resonance effects in the market. All these phenomena are fundamentally different from the traditional theoretical assumptions. Furthermore, although distributed ledger technologies such as blockchain have reduced traditional transaction costs, the sudden disruption of algorithmic liquidity supply (such as flash crashes) indicates that the digital financial market may face new types of market frictions.

This study addresses two key questions: First, what theoretical challenges does the CAPM face in the digital finance paradigm shift, and has its explanatory power weakened? Second, through which theoretical pathways does digital technology reconstruct asset pricing mechanisms? A systematic analytical framework is developed: reevaluating the market efficiency assumption of CAPM in algorithmic trading environments, analyzing the theoretical impact of platform economies on traditional asset pricing logic, and explaining how digital technology reshapes asset pricing mechanisms by altering market microstructures. This study clarifies the boundaries of traditional asset pricing theory in the digital age, laying a foundation for new theoretical paradigms. It also links digital technology with asset pricing theory, offering a conceptual framework for future research.

2. Relevant Theory and Technical Foundations

2.1 The Evolution of CAPM Theory

The Capital Asset Pricing Model (CAPM) is a pivotal theory in finance that describes the relationship between the expected return of an asset and its systematic risk. Proposed independently by William Sharpe, John Lintner, and Jan Mossin in the mid-1960s, CAPM has undergone continuous development. Its roots can be traced back to Harry Markowitz's (1952) Modern Portfolio Theory (MPT)[1]. While MPT addressed portfolio optimization, it did not explain asset pricing under equilibrium conditions. Sharpe (1964), Lintner (1965), and Mossin (1966) introduced market equilibrium conditions[2]-[4], forming the CAPM framework:

$$E\left(R_i\right) = R_f + \beta_i \times [E(R_m) - R_f]$$

Here, $E\left(R_i\right)$ is the expected return of asset i, R_f is the risk-free rate, β_i measures the asset's sensitivity to market movements, and $E\left(R_m\right)$ is the expected return of the market portfolio. The term $[E(R_m) - R_f]$ represents the market risk premium. This equation shows that an asset's expected return comprises a risk-free rate and a risk premium, which depends on systematic risk and the market risk premium. Black et al. (1972) used group testing methods[5], and Fama and MacBeth (1973) applied cross-sectional regression, both confirming the positive correlation between β coefficients and asset returns[6]. Moreover, factors like firm size and book-to-market ratios can influence asset returns, contradicting CAPM's assumption that only systematic risk determines returns. For example, Banz (1981) identified the size effect, and Rosenberg et al. found the book-to-market ratio effect [7]. To address these anomalies, scholars extended and refined CAPM. Fama and French (1993) introduced the three-factor model [8].

Building on the Fama-French three-factor model, Carhart (1997) introduced the momentum factor (MOM) to create a four-factor model [9]. Fama and French (2015) further enhanced this by adding the investment factor (CMA) and profitability factor (RMA), forming a five-factor model with greater explanatory power [10]. These advancements addressed CAPM's limitations in explaining market anomalies.

To introduce dynamic elements into theory, Harvey (1989) proposed a time-varying β coefficient model, allowing systematic risk to fluctuate with market conditions [11]. Lettau and Ludvigson (2001) incorporated the consumption-wealth ratio as a state variable, creating a more forward-looking conditional CAPM model [12]. This better captured time-varying investor expectations and risk preferences, strengthening CAPM's relevance to real-world markets. As economic globalization accelerated, CAPM theory expanded internationally. Solnik (1974) developed the International CAPM (ICAPM), incorporating exchange rate risk factors to establish a new paradigm for cross-border asset pricing[13].

2.2 Research on the Financial Innovation Char-

acteristics of Platform Economies

As an emerging economic model, platform economies have garnered significant academic attention for their unique structure and mechanisms. Rochet and Tirole (2003) pioneered the theory of two-sided markets, explaining platform pricing mechanisms and competition strategies[14]. They emphasized that platform pricing must account for network externalities in addition to costs.

In finance, Armstrong (2006) noted that financial platforms enhance market efficiency by reducing transaction costs and information asymmetry[15]. These platforms create multi-user networks, achieving scale and scope economies.

Regarding network effects, Katz and Shapiro (1985) first differentiated between direct and indirect network effects, showing a positive feedback loop between user base size and platform value in financial platforms [16]. However, Farrell and Klemperer (2007) highlighted that strong network effects can lead to market lock-in and monopoly problems, proposing the "switching cost" theory to explain user lock-in [17]. Large financial platforms often exhibit a "winner-takes-all" phenomenon, with top platforms experiencing exponential market share growth, posing new regulatory challenges. Thus, while network effects drive value creation for financial platforms, they also raise concerns about market monopolies.

2.3 Theoretical Developments and Market Impact of Algorithmic Trading

Algorithmic trading rests on several key theoretical foundations. Black and Scholes (1973) options pricing model provided the mathematical tools for subsequent algorithmic trading strategies[18]. As computer technology advanced, Demsetz (1968) demonstrated that market microstructure significantly impacts transaction costs, driving algorithmic trading technology forward[19].

Recently, Menkveld (2013) revealed the dual impact of high-frequency trading (HFT) on market liquidity [20]. Algorithmic trading enhances market efficiency by providing liquidity, but can also exacerbate market volatility due to sudden liquidity disappearances.

In terms of algorithmic trading types, Harris (2003) compared the performance characteristics of major algorithms like VWAP and TWAP, showing different algorithms suit different market conditions and trading goals [21]. Hendershott et al. (2011) found that algorithmic trading reduces information asymmetry but also alters traditional price discovery mechanisms[22]. Notably, Budish et al. (2015) proposed the "HFT arms race" theory [23]. To gain microsecond speed advantages, HFT firms invest heavily in technology upgrades. While this boosts individual trader profits, it causes resource waste and market resource misallocation from a societal perspective.

Existing research has notable gaps. First, while platform economy business models and operational features are widely studied, few works systematically explore how platform economies affect asset pricing by changing market information structures, investor behaviour, and liquidity provision. For instance, network externalities unique to platform economies may reshape risk premium formation mechanisms, and bilateral market structures may alter traditional pricing factors. Additionally, widespread user-generated content may disrupt the efficient market hypothesis. Second,2 research on algorithmic trading's impact on CAPM assumptions mostly focuses on phenomena rather than essence. Although many studies confirm algorithmic trading's effects on market liquidity, volatility, and information efficiency, few delve into the substantive challenges these microstructural changes pose to CAPM theory. Lastly, research on algorithmic trading and digital technologies in asset pricing is fragmented. Studies on individual technologies like big data analytics, AI, and blockchain lack integration. Moreover, new pricing factors (e.g., digital liquidity premiums, algorithmic co-risk) lack a unified theoretical foundation. This fragmentation hinders academic dialogue and limits the practical value of research findings. This study integrates platform economies, algorithmic trading, and digital technologies to explore new developments in asset pricing theory for the digital finance era.

3. The Impact of Digital Technology on CAPM Assumptions

3.1 Challenges to the Market Efficiency Assumption

As the core premise of the Capital Asset Pricing Model, market efficiency faces severe challenges in the era of digital technology development. On the one hand, the high-frequency trading strategy of algorithmic trading enhances market liquidity with extremely low latency and high trading speed. When market information is asymmetrical or investor sentiment is unstable, the high-frequency trading algorithm will quickly buy or sell a large amount of assets based on unverified information, causing sharp price fluctuations and affecting the market price's reflection of the true value. For instance, during the "Flash Crash" event in 2010, the rapid cancellation of orders and reverse trading by high-frequency trading algorithms led to a significant drop in the Dow Jones Industrial Average within a short period of time. On the other hand, platform enterprises hold a large amount of user data and transaction information, while ordinary investors are at a disadvantage in terms of information, leading to differences in decision-making. Some platform enterprises may

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take advantage of their information superiority to conduct internal transactions or manipulate the market, harming the interests of ordinary investors and weakening market efficiency.

3.2 Questions Raised for the Rational Investor Assumption

The popularization of digital technology has led the financial market into an era of information explosion, and investors are facing the challenge of information overload, which questions the rational investor assumption in CAPM. In today's market environment, investors need to process massive amounts of data from multiple channels in real time, which makes it extremely difficult to identify effective information and make rational decisions. Firstly, the limited nature of cognitive resources leads investors to be prone to distraction and decision-making fatigue, forcing them to shift to heuristic decision-making models. This is manifested as excessive reliance on technical pattern analysis, chasing market hotspots or imitating others' trading behaviours, while neglecting fundamental analysis and systemic risk assessment. Secondly, the unique social interaction function of digital platforms can amplify the group psychological effect and easily trigger irrational herd behaviour. Furthermore, the high speed and complexity of algorithmic trading exceed the cognitive capacity of ordinary investors, often triggering anxiety and leading to irrational behaviors such as excessive trading or panic selling. These behavioural deviations not only increase transaction costs and erode investment returns, but may also trigger unnecessary market fluctuations and exacerbate the deviation of asset prices from their intrinsic value.

3.3 Deviations from the Mean-Variance Preference Assumption

In the era of platform economy, when investors evaluate assets, they no longer only focus on expected returns and risks, but also comprehensively consider factors such as network effects and data value. Investors may be willing to pay higher valuations for platform enterprises with strong network effects. The high-frequency volatility of algorithmic trading may also change investors' perception of risks, making them focus more on short-term fluctuations and neglect long-term returns. Furthermore, the innovation-driven effect of digital technology leads to changes in the distribution of asset returns and an increase in the probability of extreme events, which is significantly different from the normal distribution assumed by the CAPM model, highlighting the limitations of the mean-variance preference assumption.

4. The Path of Digital Technology in Restructuring Asset Pricing Mechanisms

4.1 Changing Market Microstructure

Digital technology has had a profound impact on the microstructure of the market. The popularization of algorithmic trading has increased trading speed and changed the traditional manual trading model, but it has also brought challenges such as intensified market volatility. In terms of market liquidity, algorithmic trading increases market depth and liquidity by providing continuous buy and sell quotations. However, this liquidity may sharply decrease when market pressure is high, leading to significant fluctuations in asset prices. For instance, when major negative news emerges in the market or panic spreads, algorithmic traders may quickly cancel orders to avoid losses. In such cases, the liquidity in the market will sharply decrease, leading to significant fluctuations in asset prices and even market failure. In terms of information dissemination, social media and big data analysis have accelerated the speed of information spread, making market responses more timely. However, they can also easily lead to overreactions or underreactions in the market. Key information may spread rapidly among a large number of investors through social media in a short period of time, causing significant fluctuations in stock prices and increasing the complexity and uncertainty of the market.

4.2 Influencing the Risk-Return Relationship

The changes in the profit models of enterprises under the platform economy have a profound impact on asset returns. Many platform enterprises have achieved rapid growth through network effects and economies of scale. Their profit models are significantly different from those of traditional enterprises, making the value assessment of platform enterprises more complex. The intensified market volatility caused by algorithmic trading has also altered the risk-return relationship. The short-term fluctuations in high-frequency trading increase the short-term risks of assets, but they also offer more trading opportunities. In a high-frequency trading active market, there exists a complex nonlinear relationship between the short-term volatility of assets and their long-term returns. Short-term fluctuations may affect the returns of assets in the short term, but in the long run, the returns of assets still depend on their fundamental factors. Therefore, investors need to analyze the relationship between market fluctuations and asset returns more carefully and formulate reasonable investment strategies.

4.3 Restructuring Asset Pricing Logic

Based on the characteristics of digital technology, a new asset pricing logic is taking shape. Platform enterprises with strong network effects can attract more users and enhance enterprise value. The significance of data value in enterprise valuation is also increasingly prominent. By collecting, analyzing and utilizing user data, enterprises can optimize products and services and enhance operational efficiency. Furthermore, the innovation-driven effect of digital technology has made the limitations of traditional financial indicators more evident. It is necessary to introduce new valuation methods that comprehensively consider factors such as user growth, data assets, and technological innovation capabilities, in order to more accurately reflect the true value of assets. These new valuation methods will help build a more scientific and reasonable asset pricing logic, providing investors with more valuable references, and also offering new perspectives and bases for enterprises' strategic decisions and resource allocation. During this process, investors and financial institutions need to constantly learn and adapt to the new market environment, enhance their analytical capabilities and decision-making levels, in order to better cope with the opportunities and challenges brought by digital technology.

5. Empirical Design and Analysis

5.1 Empirical Design and Variable Definition

To explore the impact of digital transformation on asset pricing, this paper constructs the following OLS regression model:

$$Y_i = \alpha + \beta \times Dig_i + ?_i$$

Where Y_i represents the explained variable, which is the return on assets (ROA) or Tobin's Q value of enterprise i. Dig_i indicates the level of digital transformation of enterprise i. α is the intercept term of the model. β is the regression coefficient of digital transformation on the explained variable. $?_i$ is the random error term.

The core explanatory variable is the degree of digital transformation of the enterprise, which is quantified using a digital transformation index of the enterprise. Through principal component analysis, multiple original indicators reflecting digital transformation are integrated into a comprehensive index that fully measures the level of digitalization of the enterprise. One explained variable is the return on assets (ROA), which measures the net profit created per unit of assets of the enterprise, intuitively reflecting the efficiency of asset management and profitability of the enterprise. The higher the value, the higher the efficiency of asset utilization and the stronger the asset profitability. Another explained variable is the enterprise value, measured by Tobin's Q value, which reflects the ratio of the market value of the enterprise to its book value. The higher the Tobin's Q value, the more optimistic the market expectation for the future development of the enterprise, and the higher the market value of the enterprise relative to its book value, indicating that the competitiveness and growth potential of the enterprise in the market are stronger. The data comes from the Wind Information Database. Table 1 presents the descriptive statistics of the variables.

Table 1 presents the descriptive statistics of the variables.

VarName	Obs	Mean	SD	Min	Max
ROA	37278	0.038	0.075	-1.859	1.285
TobinQ	37278	2.077	2.425	0.611	259.146
Dig	37278	36.462	10.380	21.171	81.042

5.2 Empirical Results and Analysis

Table 2 presents the empirical results of the impact of digital transformation on asset yields or Tobin's Q values. Model 1 indicates that the coefficient of digital transformation on asset yield (ROA) is -0.000, which is significant at the 1% significance level. This implies that the impact of digital transformation on short-term asset profitability is intricate and multifaceted. High upfront costs during the early stages of transformation may lead to reduced profits and decreased ROA in the short term. Moreover, digital transformation may exacerbate market competition, prompting enterprises to adopt pricing strategies to capture market share. While this benefits long-term growth, it may compress profit margins and negatively affect ROA in the short term.

Model 2 indicates that the impact coefficient of digital transformation on enterprise value is 0.008, and it is significant at the 1% significance level. This indicates that there is a significant positive correlation between the improvement of digital transformation level and the enhancement of enterprise market value. This indicates that the improvement in innovation capabilities and operational efficiency brought about by digital transformation may lead the market to expect an increase in a company's future cash flow, thus making it willing to offer a higher

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valuation. From the perspective of the CAPM model, the impact of digital transformation on asset return rates and enterprise value reveals the limitations of traditional models in the digital age. The CAPM model assumes market efficiency, investor rationality, and mean-variance preference, but in the context of digital transformation, these assumptions are challenged. Although digital transformation may have complex impacts on asset returns in the short term, from a long-term and market value perspective, its role in enhancing enterprise value is significant. This indicates that in the era of digital finance, the level of digital transformation of enterprises may become a new factor influencing asset pricing. Traditional CAPM models need to incorporate new variables such as digital transformation to more accurately reflect market realities.

Table 2: Empirical Results of the Impact of Digital Transformation on Asset Returns or Tobin's Q

	(1)	(2)
	ROA	TobinQ
Dig	-0.000***	0.008***
	(-10.72)	(6.36)
cons	0.052***	1.796***
	(36.81)	(39.18)
N	37278	37278
R^2	0.003	0.001

Note: t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusion

This study examines the impact of the digital age on traditional asset pricing theories and the path of reconstructing pricing mechanisms, and reaches the following important conclusions: Firstly, digital technology poses a fundamental challenge to the core assumptions of CAPM. The platform economy weakens market efficiency through information asymmetry and network effects. Information overload and social interaction lead investors' behaviour to deviate from rational assumptions. However, the changes in the distribution of returns driven by innovation have shaken the mean-variance preference hypothesis. Secondly, digital technology alters the market liquidity structure through algorithmic trading, reshapes the risk premium formation mechanism through the platform economy, and reconstructs the asset pricing mechanism by creating new value assessment dimensions through data elements. This requires that new factors such as digital liquidity premium and network effect value be incorporated into asset pricing theory. Thirdly, empirical research has found that digital transformation has a significant enhancing effect on enterprise value, but it has a negative impact on short-term profitability. This reveals the complex impact of digital technology on asset pricing: although the high investment in the early stage of transformation may compress short-term profits, the market places more emphasis on the long-term growth potential it brings. Therefore, investors need to adjust their valuation methods to reflect the unique value of digital enterprises. Regulatory authorities should pay attention to the market stability impact of algorithmic trading. Enterprises need to balance the short-term costs and long-term benefits of digital transformation.

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