Asset Pricing in the Digital Economy

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Abstract. With the continuing development of the digital economy, data, platforms, and algorithms have become important and increasingly visible origins of firm value. Conventional asset pricing models in the main have reliance on financial-statement information, and they may possibly fail to fully describe the risk and return features of digital firms. On the basis of the Fama-French multifactor framework, this paper reviews the main aspects in which the digital economy changes the explanatory ability of conventional factors. It then puts forward several possible digital factors from data and algorithm aspects, including platform traffic, user scale, data assets, the proportion of quantitative trading, and the efficiency of information transmission. The bases for measuring the size, book-to-market, and profitability factors are also reconsidered, and an expanded asset pricing framework for the digital economy is developed. The analysis shows that digital factors, together with revised convention al factors, can also form a supplement to existing models when identifying the sources of value and risk exposure in digital firms. They can also provide some reference for portfolio analysis and market regulation.

Keywords: digital economy, asset pricing, digital factors, Fama-French multifactor model, explanatory power.

1. Introduction

As the newest round of technological and industrial change continues, big data, cloud computing, artificial intelligence, and internet platforms have become an important part of wider economic and business activities. The digital economy regards data as an important production element, has reliance on digital technology, and makes arrangements for resource allocation and value creation by means of network platforms (Qi and Xiao, 2020) [1]. During this process, data, platforms, and algorithms have more and more influence on firms' profitability, competitive advantages, and risk exposure. The basis used by capital markets to judge and compare firm value is changing in the same direction. Traditional pricing models in the main make use of indicators including such items as book assets, profitability, and market capitalization. Without added digital information, these models may possibly leave out important origins of value and risk.

Traditional asset pricing theories offer a basic starting method for making an explanation of asset returns, but they usually assume that financial statements can also fully show firm value. The digital economy makes this assumption weaker. Digital technology shortens the time needed for information transmission and the execution of trades. At the same time, similar algorithms may possibly increase trading in one direction and short-term volatility. In addition, the value produced by data, platforms, and technology is often not completely and consistently recognized in traditional financial statements (Qi and Liu, 2020) [2]. This paper therefore reviews how the digital economy makes changes to the explanatory ability of conventional factors and what digital indicators may possibly make a supplement to asset pricing models.

One part of the literature makes an examination of traditional asset pricing models and their factors. The capital asset pricing model gives a connection between expected returns and market risk (Sharpe, 1964) [7]. Fama and French (1993) [9] add size and book-to-market factors, Carhart (1997) [8] brings in a momentum factor, and Fama and French (2015) [10] further add profitability and investment factors. These models become a basic form of support for multifactor asset pricing studies. However, most of the indicators come from market capitalization and financial statements, and data, platforms, and algorithms receive limited attention.

Another part of the research makes a study of the digital economy and firm value. Farboodi and Veldkamp (2023) [12] give a discussion of the way in which data have an influence on firms and markets. Yu and Jiang (2024) [3], Deng et al. (2024) [4], Chen et al. (2024) [6], and Lin et al. (2025) [5] make studies of the valuation of data assets, pricing approaches, and data quality. Veldkamp (2023) [11] also explains why data need to be treated as a separate asset. Existing studies commonly focus on the value of a single data asset, but only a small number of them place data, platforms, and algorithms inside one factor-pricing framework.

This paper has three main points of contribution. For the first contribution, it makes a connection between the main value sources of digital firms, information transmission, and platform competition and asset pricing factors, and it explains why the explanatory ability of conventional factors may possibly change. For the second contribution, it gives some possible digital factors that may possibly be measured through user data, company disclosures, and market trading data, which offers more specific indicators that can also be used in later and more detailed empirical tests. For the third part, it talks about adjustments to the size, book-to-market, and profitability factors in one and the same framework, so conventional financial indicators can also better show the operating features of digital firms.

2. Main Channels Through Which the Digital Economy Affects Asset Pricing

In the digital economy, data resources, platform network effects, and algorithmic ability are in the process of becoming important and visible parts of firms' competitive advantages. These elements make changes to the way in which firm value is produced, the speed at which information enters prices, and the way market activities are organized. They therefore have an influence on the explanatory ability of conventional pricing factors.

2.1. Effects of Digital Assets on the Explanatory Power of Conventional Factors

As the digital economy continues to develop, data take a more important and more direct place in ordinary business operations. Data can also be used again, reproduced with relatively low cost, and may possibly bring increasing returns when their application range becomes wider. By means of analysis and algorithms, data also give support to product improvement, customer analysis, and risk control (Deng et al., 2024) [4]. However, data, customer relationships, and platform network effects are often not fully recognized under present accounting rules and practice. A difference may possibly then appear between book assets and the actual origins of firm value (Farboodi and Veldkamp, 2023) [12]. This difference can also make changes to the way conventional indicators, including size, book-to-market, and profitability, explain risk premia.

For size and value factors, the growth of digital firms does not have full dependence on physical assets such as factories and equipment. Operations with light assets and network effects make it possible for some small firms to enlarge their user groups and business range within a relatively short period of time. As a result, the relationship that exists between total assets and operating risk may possibly become weaker. At the same time, data resources, algorithm models, and customer relationships are not always recognized on the balance sheet, and this may possibly cause book value to be understated. A low book-to-market ratio may possibly show either growth expectations or insufficient accounting recognition of digital assets (Lin et al., 2025) [5]. Total assets and book value by themselves in many cases cannot fully measure the size and value of digital firms.

For the profitability factor and momentum effects, digital firms often make a considerable input of resources into the work of acquiring customers, building platforms, and carrying out technological research at the early stage of their business development. Present profits may possibly therefore understate their later ability to generate earnings (Yu and Jiang, 2024) [3]. Making a judgment on firm value only from current profitability may possibly miss future returns created by user accumulation and network expansion. Digital trading tools also lower the cost of information processing and trade execution. The degree of participation of quantitative strategies and individual investors may possibly then become larger, and this can also strengthen short-term momentum and trading driven by sentiment. When a trading signal becomes widely used, however, arbitrage may possibly quickly make its excess return disappear. Conventional profitability measures and past and commonly used price signals should therefore be understood together with the development stage and trading setting of a digital firm.

In general, data assets have an influence on the performance of conventional factors through such indicators as book value, firm size, and current profitability. The addition of measures of data accumulation, user networks, and algorithmic trading can also offer information that traditional models do not include.

2.2. Digital Technology and Price Discovery

Digital technology makes changes not only to the sources of information about firm value but also to the process in which information enters market prices. It can also make transaction costs lower and make information move faster, but it may possibly also strengthen one-sided trading and noise shocks. Faster trading does not always mean that pricing is more efficient in every market situation. The result also has dependence on the quality of information and the behavior of investors.

Digital trading platforms and algorithmic matching lower search and transaction costs, and they make it possible for market participants to deal with public information more quickly. Bid-ask spreads may possibly become narrower, and prices may possibly react to new information in a faster way. However, when market participants use low-quality data or when their models give similar responses to the same signal, more efficient trading may possibly appear together with price deviations.

The value of data assets changes with data updates, changes in user composition, and different application situations. Their valuation therefore has more dependence on continuing information updates (Yu and Jiang, 2024) [3]. When many investors use similar data sources and models, their trading directions may possibly become similar and increase short-term price volatility. Prices may possibly react more quickly but not move closer to fundamental value (Deng et al., 2024) [4]. Asset pricing models should therefore take financial information and also indicators into consideration such as the proportion of algorithmic trading and the delay in price adjustment, in order to identify risks linked with digital trading.

2.3. Effects of Platform Network Effects on Asset Pricing

Network externalities are a very important characteristic feature of platform economies. When the number of users becomes larger in number, a platform can also attract more merchants or service providers, and the usefulness of its products and services may possibly increase. The two-sided or multi-sided network effects that result strengthen the competitive advantages of leading platforms and may possibly place market share in the hands of a small group of firms. However, platform value does not always increase at a fixed speed. Its realization has dependence on user activity, ways of monetization, competitive conditions, and the regulatory setting.

This business model gives more importance to later user growth and long-term cash flows when firm value is judged, and it does not only look at present profits. Platform firms also face considerable and continuing uncertainty. Rules in relation to data ownership, privacy protection, and regulation have an influence on the practical range of data use. User loss, concentrated revenue sources, and stronger competition can also weaken cash-flow stability. The valuation of platform firms should therefore take the benefits from network effects and the risks connected with data compliance and user concentration into consideration. Related digital risk indicators should also be added.

3. Extending Asset Pricing Models from a Digital Economy Perspective

The analysis above shows that the digital economy has an influence on asset pricing mainly by means of the origins of firm value, the process of price discovery, and the structure of platform competition. Traditional Fama-French factors still give useful information, but indicators based only on market capitalization and financial statements cannot fully describe all of the important risk and return features of digital firms. This paper therefore puts possible digital factors into the present framework and talks about changes to the measurement of conventional factors.

The basic Fama-French three-factor model is written in the following and simplified way:

$$E(R_i) - R_f = \beta_i\left[E(RM) - R_f\right] + s_i \cdot SMB + h_i \cdot HML$$

In the digital economy, the factors above do not sufficiently describe data assets and network effects. A digital factor may possibly therefore be placed into the basic model:

$$E(R_i) - R_f = \beta_i\left[E(RM) - R_f\right] + s_i \cdot \overline{SMB} + h_i \cdot \overline{HML} + d_i \cdot DIGITAL$$

where DIGITAL has the meaning of a factor or factor portfolio made from a group of digital indicators, and di gives a reflection of how sensitive asset i is to this factor. Empirical studies may possibly first make a composite index or make tests of separate digital factors one by one.

The possible digital factors are put into two groups: factors related to data and factors related to algorithms. The first group gives a description of firms' digital resources and user networks, and the second group describes digital trading structures and the speed of information transmission.

3.1. Specification of Digital Factors

Digital factors are added for the purpose of giving a description of data assets and digital trading risks that financial statements do not fully show. For the purpose of making later empirical tests in practical research possible, candidate factors should have understandable economic meanings and should be able to be measured by the use of public information or market data that can also be obtained in practice.

3.1.1. Data dimension

Factors related to data in the main give a description of platform traffic, user scale, and data assets. These factors have relationships with user entry, the expansion of networks, and the accumulation and monetization of data. They give a description of the origins of value in digital firms at different points of the value-creation process.

Platform traffic gives a reflection of a firm's ability to attract users and keep these users. It can also be measured by the use of monthly active users, visits to websites or applications, and retention rates. High and stable traffic usually gives support to revenue from advertising, commissions, or subscriptions. However, traffic by itself is not revenue, so user quality and monetization rates must also be considered at the same time. The platform traffic factor can also be used for showing how traffic changes influence firm returns and risk.

The user scale factor makes a supplement to total assets as a way to measure firm size. Some digital firms have few tangible assets but build up strong market positions through large and continuing numbers of active users. A larger user base may possibly increase the value of interactions between users and bring more service providers to the platform (Yu and Jiang, 2024) [3]. Active users, paying users, and user growth rates can also be made use of to measure a firm's external scale. Registered users should be separated from users who are truly active.

The data asset factor gives a description of a firm's ability to collect, update, and obtain value from data resources. Possible indicators are recognized data assets, investment related to data, the ratio of data assets to total assets, and revenue from data products. The value of data has dependence on quality, timeliness, compliance, and application situations, and it should not be judged only by the volume of data. This factor helps to give a reflection of the longer-term value and uncertainty of firms driven by data (Veldkamp, 2023) [11].

3.1.2. Algorithm dimension

Factors related to algorithms give a description of market risks that may possibly come from algorithmic trading and information transmission. They have as their main contents the proportion of quantitative trading and the efficiency of information transmission. The first one gives its main attention to trading structure, and the second one pays attention to the speed at which prices take in information.

A larger proportion of quantitative trading usually makes trading activity and liquidity become larger. However, the concentrated use of similar strategies may possibly create short-term imbalances in orders. The quantitative trading share factor can also be measured through the proportion of algorithmic trading volume for individual stocks or industries and through the similarity of order directions. It can also be used to study liquidity shocks caused by strategies that become similar. Because disclosure of this data is still relatively limited, later empirical studies should give a clear statement of the data sources used and the measurement errors of proxy variables.

The information transmission efficiency factor makes a measurement of the time needed for public information to enter prices. Possible variables are the length of price adjustment after announcements, measures of price delay, and the speed of information diffusion. This factor deals with the limited attention traditional models give to information-processing mechanisms. Too many possible indicators can also make the work of factor screening and model selection become more difficult. Later research should therefore use out-of-sample and robustness tests to reduce the "factor zoo" problem (Bryzgalova et al., 2023) [14].

Table 1 presents the suggested indicators and economic interpretations of the candidate digital factors.

Table 1. Candidate Digital Factors and Their Economic Interpretations

Factor Category	Candidate Indicators	Economic Interpretation
Platform Traffic Factor	Monthly active users, visits, and user retention rate	Captures user acquisition, retention, and the basis for traffic monetization
User Scale Factor	Active users, paying users, and user growth rate	Captures network externalities, market coverage, and user growth
Data Asset Factor	Recognized data assets, data investment intensity, and revenue from data products	Captures data accumulation, updating, and monetization capacity
Quantitative Trading Share Factor	Share of algorithmic trading volume and order-direction similarity	Captures strategy convergence and short-term liquidity shocks
Information Transmission Efficiency Factor	Price-adjustment duration, price delay, and information diffusion speed	Captures the speed at which public information is incorporated into prices

3.2. Adjustments to Conventional Factors

Adding digital factors cannot fully remove measurement biases in present and commonly used indicators. Conventional factors also need to be subject to adjustments so that they show the operating features of digital firms. The basic equation above makes use of the Fama-French three-factor model. Since the five-factor model also has a profitability factor, the discussion below makes a discussion of changes to size, book-to-market, and profitability.

The size factor should make an inclusion of both the internal scale of a firm and its external network. Internal scale can also still be measured by the use of total assets and the number of employees, and external scale can also be measured through active users, paying users, and platform transaction volume. Network effects can also make external scale contribute more to firm value than a simple rise in user numbers. This contribution nevertheless has dependence on user activity and how effectively platform connections work. A revised size factor should therefore include physical inputs and the effective user base, instead of treating the number of registered users as the same thing as firm size.

Changing the book-to-market factor has a need for additional and more detailed information about digital assets. Spending on data collection, algorithm improvement, and user operations may possibly be recognized as current expenses. Book value may possibly then fail to give a reflection of intangible capital built over a relatively long time (Gulen et al., 2025) [13]. Data assets also differ from traditional intangible assets such as patents, because their value depends on continuing updates, lawful use, and particular application situations. Data assets that meet recognition conditions may possibly be added to book value, with other changes based on data-related investment and revenue from data products. Not every digital expense should be made into capital. This method can also make the difference that exists between book value and the resources a firm actually controls smaller (Lin et al., 2025) [5].

The profitability factor should give a reflection of present profits and later monetization ability. Digital firms may possibly deliberately keep present profits low during customer acquisition and platform development, but this does not ensure later profitability. Besides operating profit and cash flow, analysts may possibly take active-user growth, customer retention, revenue per user, and customer acquisition cost into consideration. These indicators have pricing relevance only when user growth can also become stable revenue and cash flow. In general, the size factor should include the effective user base, the book-to-market factor should add recognizable digital assets, and the profitability factor should make a combination of user operating indicators with actual monetization ability.

4. Conclusions and Recommendations

This paper makes a review of whether traditional asset pricing models can also be used in the digital economy. The analysis gives the result that data, platforms, and algorithms influence the origins of firm value, the speed at which information moves into prices, and market trading structures. These changes bring new and more obvious limits to the interpretation of conventional indicators such as size, book-to-market, and profitability. This paper therefore puts forward platform traffic, user scale, data assets, the proportion of quantitative trading, and information transmission efficiency as possible digital factors, and it changes the measurement of conventional factors. This framework makes a supplement to present ways of identifying the origins of value and risk exposure in digital firms. However, its effectiveness still needs to be tested with actual market data.

Investors should make use of digital indicators together with cash-flow measures and ordinary valuation measures. Firm value should not be judged only from user numbers, technology investment, or digital labels. Investors can also make continuous tracking of active users, retention rates, revenue per user, data-compliance costs, and crowding in algorithmic trading, and they can also judge whether these indicators become revenue and cash flow. When investors are building portfolios, investors can also watch common exposure to data assets and algorithmic trading in order to make liquidity risk lower caused by the concentration of similar strategies.

Firms should make the establishment of data-asset registers that can also be traced and that state data sources, update frequencies, usage rights, and main and possible application situations. They should also make use of consistent and comparable statistical definitions for user scale, user activity, and monetization indicators. When they disclose digital investment, firms should make a separation between maintenance spending and investment that may possibly produce long-term returns. Ordinary technology spending should not be described again as data assets. Clearer disclosure helps investors make a judgment on whether digital resources can also bring stable returns.

Regulators can also gradually make a standardization of the recognition, measurement, and disclosure of data assets. They can also give statements on disclosure requirements for platform user indicators and digital operating indicators, and they can also make a strengthening of the monitoring of algorithmic trading concentration, the similarity of order directions, and unusual liquidity. Regulation should avoid the situation of undervaluation caused by missing data assets and the overvaluation caused by digital indicators without an earnings basis. These measures can also make comparison across digital firms more workable.

This paper is still mainly theoretical at the present stage. It does not make the construction of directly tradable factor portfolios or make direct tests of whether the proposed digital factors explain returns. Some indicators may possibly overlap. For example, platform traffic, user scale, and data-asset accumulation often have influence on each other. Data about quantitative trading and company data assets also cannot always be obtained. Later research can also make use of information from China's A-share market and international markets to give methods for factor construction, compare the out-of-sample performance of composite and individual factors, and make tests of their connections with conventional factors, robustness, and range of use.

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