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Digital Finance and Pricing Efficiency in China's A-share Market

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Abstract. Using 37,269 firm-year observations for Chinese non-financial A-share listed firms during 2012-2023, this study investigates whether regional digital financial development changes the efficiency with which equity prices incorporate information. Stock price synchronicity (SYNCH) is adopted as the inverse proxy for pricing efficiency, while the Peking University Digital Financial Inclusion Index (DIF) is used to measure the development of digital finance at the regional level. The empirical evidence shows that DIF is positively and significantly related to SYNCH after controlling for province-by-year shocks and firm listing age. In other words, greater digital financial development is associated with stronger stock return co-movement rather than a clear improvement in firm-specific pricing. The heterogeneity tests further indicate that this effect is concentrated among large-cap firms. These results support a passive-indexing interpretation: as digital financial tools and index products expand, large constituent stocks become more exposed to common fund-flow and information shocks. The findings imply that easier access to financial information does not automatically enhance market efficiency; the final effect depends on how information is distributed and how trading is organized.

Keywords: Digital finance, Pricing efficiency, Stock price synchronicity, Passive indexing

1. Introduction

Efficient pricing is central to the allocative role of the capital market. When share prices respond to firm-level fundamentals in a timely way, capital is more likely to be directed toward firms with stronger productivity and growth prospects. Over the past decade, China's financial environment has been reshaped by mobile payment systems, online wealth-management products, robo-advisory tools, and financial information apps. These technologies have reduced participation costs and, at the same time, altered the channels through which investors receive information and update beliefs.

A conventional view is that financial deepening and information technology improve market efficiency by reducing information frictions and enabling more firm-level news to enter prices. Stock price synchronicity is often used in this literature because a stock whose return is mainly explained by market-wide or industry-wide movements contains less firm-specific information. Yet the implications of digital finance are not one-sided. The same platforms that broaden access to information may also centralize attention, standardize narratives, and encourage similar trading decisions. Whether digital finance reduces or raises SYNCH is therefore an empirical question.

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This question is especially relevant in China. Retail investors remain highly active, and their decisions are often influenced by short-horizon news and market sentiment. At the same time, a small group of financial platforms, including East Money, Tonghuashun, and Xueqiu, has become an important gateway for market information and investor discussion. Since 2018, the expansion of ETFs and other passive products has added another layer of common trading pressure. These features suggest that digital finance may improve access to information while also strengthening homogeneous information exposure and synchronized trading.

This study examines the issue with a panel of Chinese non-financial A-share firms from 2012 to 2023. The analysis combines a two-way fixed effects framework with year-specific cross-sectional regressions to trace both the average relation and its evolution over time. The empirical design uses the full A-share sample, controls for province-by-year shocks, and clusters standard errors at the city level. In doing so, it provides evidence on how digital finance may influence pricing efficiency through the growth of passive indexing in the Chinese market.

2. Literature review and hypothesis development

2.1. Pricing efficiency and stock price synchronicity

The pricing-efficiency literature emphasizes the extent to which stock prices embed information about individual firms. When returns are largely driven by aggregate market or industry factors, the price is less informative about firm-specific conditions [1]. Cross-country evidence also shows that markets with weaker investor protection and less transparent information environments tend to have higher return synchronicity [2]. From a real-economy perspective, the information content of stock prices matters because it affects how capital is allocated across firms [3]. Following this logic, SYNCH is treated here as a negative indicator of pricing efficiency: a higher value means that less idiosyncratic information is reflected in the stock price [4].

2.2. Digital finance

Prior work on digital finance has paid considerable attention to corporate financing, innovation activity, and household entrepreneurship. The Peking University Digital Financial Inclusion Index has become a widely used measure for capturing regional differences in digital financial development [5]. Empirical studies show that digital finance can stimulate entrepreneurial activity [6, 7], ease financing constraints, and support technological innovation by firms [8, 9]. Less is known, however, about its consequences for capital market pricing, particularly about whether its effect changes as digital platforms and index-based products become more mature.

2.3. Mechanism and research hypothesis

The effect of digital finance is likely to vary across stages of market development. At an early stage, its main contribution is to make information cheaper and easier to obtain. Li et al. show that digital finance can improve firm information transparency, which enables ordinary investors to access announcements, financial data, and research opinions at lower cost; such a process should help firm-specific news enter prices and reduce SYNCH [10]. At a later stage, however, the marginal effect may come less from information availability and more from the architecture of information distribution and trading tools [11]. Investor attention can cluster around the same popular stocks through search engines and financial platforms [12]. ETF growth can transmit common fund-flow

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shocks to constituent stocks, and common institutional ownership can raise return co-movement across firms [13, 14]. These channels indicate that digital finance may also increase synchronicity once the market becomes more platform- and index-driven.

The mechanism tested in this study centers on passive indexing. As ETFs and index products expand, constituent stocks are traded together according to index weights. This trading rule creates common flow shocks, so individual stock returns may move together even when firm-specific information differs. Evidence from Ben-David et al. suggests that larger ETF ownership can amplify volatility and co-movement in the underlying stocks [13]. Because large-cap firms are more likely to be included in major indexes and ETF portfolios, they should be more exposed to this channel. The main hypothesis is therefore that the positive relation between digital finance and SYNCH is stronger for large-cap firms.

3. Research design

3.1. Sample and data

The initial sample consists of Chinese A-share listed firms over 2012-2023. Financial firms and ST/*ST firms are removed, and continuous variables are winsorized at the 1st and 99th percentiles. Weekly stock returns, financial statement variables, and firm characteristics are collected from the East Money Choice terminal. Digital finance is measured by the Peking University Digital Financial Inclusion Index and matched to firms by registered city. Weekly returns of the CSI 300 Index are used as the market return, and weekly returns of the Shenwan first-level industry index are used as the industry return. The broad sample contains 4,762 firms and 37,269 firm-year observations, while the narrower sample with complete financial controls for medium- and large-cap firms contains 16,662 observations.

3.2. Variable construction

The outcome variable captures stock market pricing efficiency. The main measure is stock price synchronicity (SYNCH). For each firm-year, weekly individual stock returns are regressed on the weekly CSI 300 return and the relevant Shenwan first-level industry return. The R^2 from this return model is then transformed as follows:

$$SYNCH = ln\left[R^2/\left(1-R^2\right)\right] \tag{1}$$

A larger SYNCH means that a greater share of individual stock variation is explained by common factors, and therefore that the stock price contains less firm-specific information. As a supplementary outcome, this study uses idiosyncratic volatility (IVOL), measured as the annual standard deviation of the residuals from the same return model. The key explanatory variable, DIF, is the standardized aggregate Digital Financial Inclusion Index. The control set includes SIZE, LEV, ROA, GROWTH, BM, TOP1, INST, TURN, and AGE, which capture firm scale, leverage, profitability, growth, valuation, ownership concentration, institutional holdings, trading activity, and listing age.

3.3. Empirical model

The baseline specification is written as follows:

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$$SYNCH_{it} = \alpha + \beta \bullet DIF_{ct} + \gamma \bullet Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

In this equation, i indexes firms, c indexes cities, and t indexes years. Firm fixed effects μ_i control for time-invariant firm characteristics, while λ_t denotes province-by-year fixed effects. The latter absorb province-level time-varying shocks such as economic growth, industrial policy, and macroeconomic conditions. Due to DIF varies at the city-year level, standard errors are clustered by city to account for within-city correlation across listed firms. Additional specifications with industry-by-year fixed effects are also estimated as robustness checks.

4. Empirical findings

4.1. Descriptive evidence

Table 1 summarizes the main variables. The average SYNCH in the broad sample suggests that the overall level of firm-specific pricing is higher than in the earlier selected sample, and the dispersion of the variable is sufficiently large for cross-sectional analysis. IVOL falls within the range commonly observed in A-share studies. The financial controls in the narrower sample also show plausible distributions, indicating that the sample is suitable for regression analysis.

Table 1. Descriptive statistics

Variable	N	Mean	SD	Min	Median	Max
SYNCH	37,269	−0.338	1.071	−3.823	−0.301	1.467
IVOL	37,269	0.043	0.020	0.015	0.040	0.151
DIF (std)	37,269	0.000	0.864	−2.234	0.103	1.476
SIZE	37,269	23.421	1.623	19.480	23.310	28.181
LEV	16,662	0.464	0.196	0.062	0.476	0.864
ROA	16,662	0.062	0.063	−0.051	0.052	0.290
GROWTH	37,269	0.152	0.312	−0.380	0.108	1.430
BM	16,662	0.435	0.295	0.047	0.366	1.432
TOP1	16,662	0.388	0.169	0.078	0.376	0.802
INST	16,662	0.527	0.241	0.014	0.571	0.932
TURN	16,662	5.683	0.912	3.371	5.724	7.681
AGE	37,269	2.341	0.721	0.000	2.485	3.367

Note: Summary statistics are reported for the variables used in the empirical analysis. Continuous variables are winsorized at the 1st and 99th percentiles.

4.2. Baseline results

Table 2 presents the baseline estimates. Each model includes firm fixed effects, and the reported standard errors are clustered at the city level. After absorbing regional time-varying factors, DIF remains positively associated with SYNCH in M1 and M2. The result indicates that digital finance is linked to stronger return co-movement rather than lower synchronicity. This pattern is consistent

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with the passive indexing mechanism, under which the expansion of ETFs and passive products makes common fund flows more important for individual stock returns.

Table 2. Baseline regression results

Variable	M1 SYNCH	M2 SYNCH (prov×yr)	M3 SYNCH (ind×yr)
DIF	+0.226** (0.105)	+0.324** (0.156)	+0.177 (0.108)
AGE	+0.352*** (0.022)	+0.318*** (0.021)	+0.289*** (0.023)
Firm FE	Yes	Yes	Yes
Year FE type	Year	Province×Year	Industry×Year
City cluster SE	Yes	Yes	Yes
Observations	37,269	37,269	37,269
Within R^2	—	0.012	—

Note: Robust standard errors clustered at the city level appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

4.3. Time-varying coefficients and size-related patterns

To examine whether the relation changes over time, the study estimates separate cross-sectional regressions for each year and records the annual coefficient β. Table 3 shows no simple linear trend: the estimated coefficients switch signs across years. The negative coefficients during 2012-2015 are consistent with an early information-access effect that improves pricing efficiency. By contrast, the coefficient becomes significantly positive in 2016, significantly negative in 2019, and significantly positive again in 2020, while the other years are statistically insignificant. This pattern suggests that the broad information benefits for small firms may offset localized positive co-movement shocks, and it may also reflect the influence of year-specific macro conditions.

Table 3. Year-by-year cross-sectional coefficients

Year	β(DIF)	95% CI	Observations	Significance
2012	−0.045	[−0.183, 0.093]	2,090	
2013	−0.002	[−0.146, 0.142]	2,152	
2014	−0.016	[−0.181, 0.149]	2,194	
2015	−0.095	[−0.232, 0.042]	2,362	
2016	0.170	[0.010, 0.331]	2,447	*
2017	−0.006	[−0.148, 0.135]	2,853	
2018	0.085	[−0.027, 0.196]	3,150	
2019	−0.124	[−0.225, −0.023]	3,285	*
2020	0.105	[0.006, 0.203]	3,532	*
2021	0.015	[−0.105, 0.135]	4,046	

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Table 3. (continued)

2022	0.008	[−0.085, 0.102]	4,422
2023	0.022	[−0.075, 0.119]	4,736

Note: Annual coefficients are estimated from separate cross-sectional OLS regressions with White heteroskedasticity-robust standard errors.

4.4. Size heterogeneity: interaction specification

The size channel is tested by adding an interaction term to the province-by-year fixed effects model with city-level clustered standard errors:

$$SYNCH_{it} = \alpha + \beta_1 \bullet DIF_{ct} + \beta_2 \bullet DIF_{ct} \bullet Large_{it} + \gamma \bullet AGE_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Large is defined according to the yearly median of SIZE; it equals one for large-cap observations. The coefficient β_1 captures the DIF effect for the small-cap group, and $\beta_1 + \beta_2$ captures the corresponding net effect for large-cap firms. As reported in Table 4, the interaction term is positive and highly significant, which means that the effect of DIF is stronger among large-cap firms. This result fits the passive-indexing argument: large firms are more frequently included in indexes and ETF portfolios, so they bear a larger share of common passive flow shocks. It is also consistent with Farboodi et al., who argue that data-driven institutional information advantages are concentrated in large stocks and can increase exposure to common information shocks [15]. The same conclusion appears when lagged DIF is used.

Table 4. Size heterogeneity: interaction model

Model specification	Coefficient	t / N	Significance
DIF (small-cap baseline, β_1)	+0.244 t=1.58, N=37,269, p=0.115		Not significant (p=0.115)
DIF×Large (size diff, β_2)	+0.123*** t=+10.94, N=37,269	Large-cap net=+0.367 (directional, no joint test) N = 16,662	Significant
Lagged DIF×Large (β_2, Model 4)	+0.170*** t=+11.91, N=32,533	Lagged DIF×Large only N = 32,533	Significant

Note: The interaction specification is $SYNCH = \alpha + \beta_1 DIF + \beta_2 DIF \times Large + \gamma AGE + firm\ FE + province \times year\ FE$. Large equals one when SIZE is above the annual median. Model 4 uses lagged DIF. Standard errors are clustered by city. *** p<0.01.

4.5. Mechanism analysis: from wider access to synchronized trading

The mechanism evidence points to passive indexing. Ben-David et al. document that ETF ownership can make constituent stocks move more closely together [13]. In an index product, trading is tied to index weights, so fund inflows and outflows affect many component stocks simultaneously. As ETF assets grow, this common trading pressure can outweigh firm-level information in short-run price

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movements. The significant large-cap interaction is therefore informative: firms that are more likely to be index constituents display a stronger DIF-SYNCH relation, exactly where the passive-indexing channel should be most visible.

4.6. Robustness analysis

Table 5 reports two robustness checks under the same firm fixed effects, province-by-year fixed effects, and city-clustered standard error structure. First, replacing current DIF with its one-period lag leaves the main result intact, which reduces concerns that current synchronicity mechanically drives contemporaneous digital finance. Second, using IVOL as an alternative dependent variable gives a coefficient with the expected opposite sign. The evidence from SYNCH and IVOL therefore points to the same interpretation.

Table 5. Robustness checks

Test	β(DIF)	t statistic	Observations
Full sample	+0.324**	2.08	37,269
Lagged DIF	+0.299***	2.71	32,533
Alternative dependent variable: IVOL	−0.0069**	−2.15	37,269

Note: Standard errors are clustered at the city level. ***, **, and * correspond to the 1%, 5%, and 10% significance levels.

5. Conclusion

This study uses 37,269 firm-year observations for Chinese non-financial A-share listed companies from 2012 to 2023 to examine how digital financial development relates to stock market pricing efficiency. The main finding is that DIF raises SYNCH after controlling for province-by-year shocks and city-level error correlation. Thus, in this setting, digital finance is not simply a force that improves the incorporation of firm-specific information. It may also intensify common pricing forces through platform-based information channels, thematic trading, and passive indexing. The effect is considerably stronger for large-cap firms, which indicates that firm size amplifies the relation between digital finance and synchronicity. Overall, the results show that more accessible information does not necessarily mean more diverse information. The market impact of digital finance depends on platform structure, investor behavior, and the trading vehicles through which capital is allocated.

The findings have several policy implications. Regulators should support digital financial innovation while also monitoring the possibility that platforms and index products make investor behavior more homogeneous. Financial information platforms should disclose information sources more clearly and improve the transparency of recommendation and ranking mechanisms, so that market narratives are not dominated by a small number of platform signals. At the same time, the growth of ETFs and passive index products should be evaluated for its effects on constituent-stock co-movement, especially in industries where thematic trading is strong. Investor education is also important: retail investors need to distinguish access to information from the quality and diversity of information. Institutional investors, meanwhile, should be encouraged to strengthen long-horizon fundamental research and differentiated valuation.

Several limitations remain. The sample covers the main A-share market but excludes the STAR Market and the Beijing Stock Exchange, and some regressions use a reduced sample because of

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missing financial controls. The mechanism test is also indirect, since it relies mainly on size heterogeneity rather than direct ETF holding data, index reconstitution events, or subscription and redemption flows. Future work could use exogenous shocks such as broadband infrastructure rollout or digital financial inclusion pilots, and could combine ETF portfolio data, platform-level information diffusion, and investor trading records to identify the channels more directly.

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