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The way digitalization is impacting international financial markets: Stock price synchronicity

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Abstract

This paper investigates whether and how the development level of a country's digital economy affects stock price synchronicity. The results indicate that countries with high levels of digital economy development exhibit low stock price synchronicity. Additionally, by decomposing stock price synchronicity into systematic and firm-specific stock return variations, we find that systematic (firm-specific) variations of stock returns decrease (increase) with the level of a country's digitalization. These findings shed light on the future trend of stock price synchronicity in financial markets around the world and support the information-based interpretation of stock price synchronicity.

KEYWORDS

digitalization, capital market, stock price informativeness, stock price synchronicity

JEL CLASSIFICATION

G10, G14, G15, O16, O33

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1 | INTRODUCTION

Stock price synchronicity, the extent to which stock prices move together, is a critical issue in market efficiency, asset pricing, and portfolio analysis (Eun et al., 2015; Morck et al., 2013; Wurgler, 2000). Previous studies attribute cross-country differences in stock price synchronicity to factors that lead to varied levels of firm-specific information exploration and its incorporation into stock prices, such as investor property rights and information disclosure policy (e.g., Dang et al., 2015; Morck et al., 2000). Accordingly, digitalization, as a trend that reduces the complexity and costs of collecting and processing information (e.g., Banker et al., 2002; Barber & Odean, 2001; Cai, 2018; Knudsen, 2020; Mollick, 2014), should elevate the capitalization of firm-specific information into stock prices and thus decrease stock price synchronicity.[1] However, this prediction has not been empirically explored. Given that digitalization is expected to increase, and thus continue altering financial markets, understanding the impact of the level of digital economy development on stock price synchronicity can help predict the future condition of financial markets.

Additionally, although many studies theoretically and empirically indicate that high stock price synchronicity is associated with a relatively lower capitalization of firm-specific information (compared with marketwide information) into stock prices (e.g., Y. Dong et al., 2016; Durnev et al., 2003, 2004), this view has been challenged by other research (e.g., Chan & Chan, 2014; Dasgupta et al., 2010). These contrasting views about stock price synchronicity warrant investigation, and our study sheds light on this debate. Most previous studies investigate stock price synchronicity by linking it with a specific type/source of firm-specific information. Two common issues make these findings difficult to interpret. First, because stock prices respond to all the information available in the market, which can arrive almost simultaneously, it is almost impossible to differentiate the effects of different types of information. Second, there is potential endogeneity between firm-specific information disclosure and firms' stock price informativeness.[2] Exploring how the advancement of the level of digitalization in a country affects stock price synchronicity avoids these two common issues because such development has wide impacts on different types of firm-specific information and is an exogenous factor that is not subject to firm characteristics.

To shed light on the future trend and economic meaning of stock price synchronicity, we investigate the effect of a country's digital economy development level on the synchronous movements of stock prices. Motivated by the information-based explanation of stock price synchronicity (Durnev et al., 2003; Jin & Myers, 2006; Morck et al., 2000; Roll, 1988; Veldkamp, 2006), we propose four testable hypotheses about the effects of a country's level of the digital economy on its stock price synchronicity.[3] First, a high level of the digital economy reduces the costs associated with information collection and processing, facilitates information dissemination, and thus decreases stock price synchronicity. Second, a high level of digital economy development decreases systematic stock return variation by dampening noise trading. Third, a high digital economy development level has no consistent effect on firm-specific stock return variation, since the latter is positively associated with both the amount of firm-specific information capitalized into stock prices and noise trading. Fourth, a high development level of the digital economy has a positive effect on firm-specific stock return variation after controlling for systematic stock return variation, since the association between firm-specific stock return variation and noise trading weakens after controlling for systematic stock return variation (Aabo et al., 2017). Our results support all four hypotheses.

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Using the Networked Readiness Index (NRI) as a measure of a country's digitalization level (Moeini Gharagozloo et al., 2020), we find a significant negative relation between stock price synchronicity and the development level of the digital economy. Specifically, a one standard deviation increase in the NRI decreases our R^2-based stock price synchronicity measure by 1.0448 standard deviations. Moreover, adding the NRI to the model increases the adjusted R^2 by around 20%. The result based on our alternative stock price synchronicity measure is similar. Furthermore, we find that the NRI has a significant negative impact on systematic stock return variation, indicating that a high NRI decreases stock price synchronicity by reducing noise trading.[4] In contrast, the NRI has no substantial influence on firm-specific stock return variation. Furthermore, the effect of the NRI on firm-specific stock return variation is (positively) significant after controlling for systematic stock return variation, which is also consistent with our hypotheses. Finally, due to multicollinearity concerns raised by high correlations between the NRI and some control variables (e.g., the gross domestic product, or GDP, per capita, and the good government index), we run robust tests using the orthogonal NRI, which is estimated by regressing the NRI on these highly correlated control variables.[5] Our results stay the same, indicating that our main results are not contaminated by high correlations between the NRI and other control variables.[6]

Our study contributes to the literature in three ways. First, to the best of our knowledge, this study is the first to examine the relation between the development level of the digital economy in a country and stock price synchronicity. Given that digitalization is expected to persist and occur internationally, our findings suggest that the declining trend for stock price synchronicity, shown by Morck et al. (2000) and Campbell et al. (2001), will persist and expand from developed countries to developing countries, leading to many important implications for corporate investment and the asset management industry.[7] Second, our study supports the view that lower stock price synchronicity indicates greater capitalization of firm-specific information into stock prices (e.g., Dang et al., 2015; Eun et al., 2015; Jin & Myers, 2006; Morck et al., 2000). Third, by investigating the relation between the level of digitalization in a country and two components of stock price synchronicity—namely, market-level return variation and firm-specific variation—we shed light on the drivers behind these variations. Our findings support the views that systematic return variations are caused by noise trading (e.g., Aabo et al., 2017; Morck et al., 2000) and that firm-specific variation reflects both noise trading and the amount of firm-specific information capitalized into stock prices (Aabo et al., 2017). Our findings also support the argument of Li et al. (2014) that firm-specific variation (i.e., the variance of residual returns from a market model) and stock price synchronicity (i.e., the R^2 measure from a market model), which some papers use equivalently to each other, are not interchangeable.

The remainder of the paper is organized as follows. Section 2 develops our hypotheses. Section 3 discusses the data and methodology. Section 4 presents the results. Section 5 concludes the paper.

2 | HYPOTHESIS DEVELOPMENT

2.1 | Stock price synchronicity and firm-specific information

Roll (1988) argues that the extent to which stocks move together, known as stock price synchronicity, depends on the relative amount of market- and firm-level information capitalized into stock prices. Therefore, a relatively high (low) amount of market-level information capitalized

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into stock prices leads to high (low) levels of stock price synchronicity. In line with this view, previous studies find that cross-country variations in stock price synchronicity can be attributed to good institutional characteristics and a transparent information environment, which facilitate capitalizing firm-specific information into stock prices (e.g., Dang et al., 2015; Y. Dong et al., 2016; Eun et al., 2015; Morck et al., 2000). This explanation is also theoretically supported by Jin and Myers (2006) and Veldkamp (2006). According to this view, the level of stock price synchronicity is positively associated with the complexity and costs of exploiting firm-specific information. A contradicting view argues that high stock price synchronicity indicates more informative stock prices because events come as little surprise to investors (e.g., Dasgupta et al., 2010; Kelly, 2014). These conflicting views warrant investigation and motivate this study.

Most previous studies link stock price synchronicity to specific types/sources of firm-specific information, such as seasonal equity offerings or stock analysts. Although this stream of studies tries to identify how stock price synchronicity responds to the disclosure of certain information, given the features of stock price synchronicity, such results are difficult to interpret, for the following two reasons. First, as an ultimate response to investors' trading activities, stock returns reflect the aggregate of investors' beliefs about all the information in the market, both public and private. Therefore, it is hard to know which information stock prices are really responding to as it is almost impossible to differentiate the effects of specific types/sources of firm-specific information from other simultaneously arriving information (e.g., part of the arriving information could be private, and the public might not even be aware of its existence).

It is worth noting that public information could produce new private information, which is largely ignored by previous studies.[8] For example, a skilled fund manager could have insightful and unique views about publicly available information, such as 10-K financial statements. Unlike inside information, this type of private information is not subject to governance conditions or firm characteristics and is thus very hard for academic research to identify/control for. Second, there is potential endogeneity between specific types/sources of firm-specific information and firm stock price informativeness. For example, although the number of analysts is typically considered an indicator of high informativeness, it can also signal the complexity of a firm's information (i.e., low informativeness), because higher information processing demands would attract more services (i.e., numbers of analysts). Firms with high numbers of analysts are more likely to have low stock price informativeness (i.e., high stock price synchronicity) if the analysts cannot improve upon the informativeness as expected. Similarly, according to signalling theory, firm managers can make specific decisions (e.g., seasonal offerings) based on their expected firm information conditions, causing endogeneity between stock price informativeness and specific information announcements.

Therefore, examination of the effects of exogenous factors, which affect all firm-specific information and are exogenous to firms' information announcement decisions, helps us to understand the relation between stock price synchronicity and stock price informativeness. We argue a country's digital economy development level is one such factor.

2.2 | Development level of the digital economy and firm-specific information

The digital economy has been rapidly developing since the beginning of the 21st century. According to the definition developed by the Bureau of Economic Analysis, the digital economy

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includes (1) the digital infrastructure needed to enable the existence and operation of computer networks, (2) the digital transactions that take place using that system, and (3) the content that digital economy users create and access (Barefoot et al., 2018). Similarly, MATEC Web of Conferences defines a digital economy as a kind of economy characterized by the active implementation and application of digital technologies for the collection, storage, processing, transformation, and transmission of data in all areas of human activity (Borremans et al., 2018).

The development of the digital economy has dramatically changed how investment information is produced, stored, transmitted, processed, and analyzed. For example, digitalization affects the accounting field, which plays an important role in financial information collecting, production, and processing, in terms of its boundaries, influence, and production of information (Knudsen, 2020). In addition, given the high development levels of the digital economy, business and financial information are stored digitally as machine-readable data, allowing users to easily search, collect, and process it. Moreover, digitalization affects information processing and analysis through innovations such as artificial intelligence and other types of quantitative algorithms, which are being increasingly used for investment analysis (Jung et al., 2018; Shanmuganathan, 2020).

These changes through digitalization have significantly reduced the complexity and costs of information analysis, affecting the extent to which stock prices move together. Obviously, the level of digitalization will impact the capitalization of public information into stock prices. For example, eXtensible Business Reporting Language (XBRL) is a standard software language that was developed to improve financial data communications, making it easier to compile and share these data, and is therefore considered a part of business digitalization. Y. Dong et al. (2016) demonstrate that the adoption of XBRL for filing financial statements, which is required by the US Securities and Exchange Commission, increases the amount of firm-specific information capitalized into stock prices. In addition, a more developed digital economy facilitates the production of new information based on existing information by assisting in information analysis. Digitalized data and new data analysis tools (e.g., artificial intelligence and other types of algorithms) greatly simplify the data analysis.

Given that the development level of the digital economy reduces the complexity and costs associated with information production, transmission, and processing, it affects a wide range of investment information, from public information (e.g., financial statements and investment reports) to private information (e.g., private views and investment strategies). Although both marketwide and firm-specific information are affected, market and industry information are less complex and costly to gather and process relative to firm-specific information, because it does not require access to large numbers of firm-level information sources and the costs can be shared among all the firms in the market. Therefore, the development level of the digital economy should have a stronger effect on the capitalization of firm-specific information than on the capitalization of marketwide information.

Given the notions presented above, we argue that the development level of the digital economy facilitates the capitalization of firm-specific information into stock prices.

2.3 | Development level of the digital economy and stock price synchronicity

We develop our hypotheses based on the view that low stock price synchronicity indicates relatively high levels of capitalization of firm-specific information (Chen & Doukas, 2022; Crawford et al., 2012; Durnev et al., 2004, 2003; Jin & Myers, 2006; Morck et al., 2000). As

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discussed in Section 2.2, although digital development can simultaneously reduce the cost/complexity of exploiting both marketwide and firm-specific information, it leads to relatively high levels of capitalization of firm-specific information into stock prices, since marketwide information should be more readily available, even without digital development. Therefore, we expect to observe a negative relationship between a country's level of development of the digital economy and its stock price synchronicity. A counterview holds that a country's digital economy development level could have an opposite effect on stock price synchronicity. According to this view, since a high digital economy level facilitates information dissemination, it can a) reduce investors' incentive to collect information, given fast and easy information dissemination, and b) lead to herding behaviour among investors if they trade on the same set of information. Whether digital development decreases stock price synchronicity is thus an empirical issue that warrants investigation. Given the discussion above, we formalize the first hypothesis as follows.

H1 *A country's digital economy development level has a negative effect on the extent to which stock prices move together in that country.*

To further understand the drivers of the relation between the digital economy development level and stock price synchronicity, we decompose stock price synchronicity into two components: systematic stock return variation (i.e., stock variation driven by market variation) and firm-specific stock return variation. Morck et al. (2000) and Aabo et al. (2017) show that high levels of noise trading lead to high systematic stock return variation. If high levels of digital economy development decrease stock price synchronicity through improving the transparency of firm-specific information, it should dampen the noise trading level and thus lead to low systematic stock return variation. Our second hypothesis is thus stated as follows.

H2 *A country's digital economy development level has a negative effect on the systematic stock return variation in that country.*

Furthermore, we examine the relationship between the digital economy development level and firm-specific stock return variation. Roll (1988) suggests that firm-specific variation can reflect (1) the capitalization of firm-specific information into prices by informed trading and/or (2) noise trading. The empirical findings are conflicting. Some studies find a positive relation between firm-specific variation and the capitalization of firm-specific information into prices (e.g., Durnev et al., 2004; Jiang et al., 2009; Zhang et al., 2016), whereas others show a positive relation between firm-specific variation and noise trading (e.g., Aabo et al., 2017; Krishnaswami & Subramaniam, 1999; Pontiff, 2006). These conflicting findings suggest that greater firm-specific return variation can capture noise trading in some situations and the capitalization of firm-specific information under other circumstances. High levels of digital economy development encourage the exploitation of firm-specific information and improve its transparency. Thus, the effect of the digital economy development level on firm-specific stock return variation is unclear; the effect depends on which component is more important in the stock return variation. Although we could find a positive, negative, and no effect of the digital economy development level on firm-specific stock return variation, for testing purposes, we hypothesize that the digital economy development level has no effect on firm-specific stock return. Thus, our third hypothesis is stated as follows.

H3 *A country's digital economy development level has no consistent impact on the firm-specific stock return variation in that country.*

Aabo et al. (2017) find that the strength of the association between firm-specific stock return variation and noise trading decreases after controlling for marketwide variation, indicating that firm-specific stock return variation is more likely to reflect the capitalization of firm-specific information into prices when marketwide variation is controlled for. Therefore, we expect to observe a positive effect of the digital economy development level on firm-specific stock return variation after controlling for systematic stock return variation, because high development levels of the digital economy facilitate the capitalization of firm-specific information. Thus, our fourth hypothesis is formalized as follows.

H4 *After controlling for systematic stock return variation, we find a country's digital economy development level has a positive effect on the firm-specific stock return variation in that country.*

3 | DATA AND METHODS

3.1 | Stock price synchronicity

We measure stock price synchronicity following the procedure of Morck et al. (2000). Our first measure of stock price synchronicity, *SYNCH*, is the proportion of individual stock returns that can be explained by market returns. We first estimate the stock-level *SYNCH* value, which is the R^2 value of the following regression:

$$r_{i,t} = a_i + \beta_{j,i} r_{j,t} + \beta_{us,i} r_{US,t} + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$, $r_{j,t}$, and $r_{US,t}$ are the weekly returns of individual stock i, country j's stock market, and the US market, respectively. Country j's stock market return is measured by the corresponding MSCI country index return and the US market return, defined as the Center for Research in Security Prices (CRSP) value-weighted index return. For each stock i in a given year, we run the regression using the return data in that year. When estimating stock-level *SYNCH* values, we also require the stocks to have at least 25 valid observations in the period. Next, we calculate the average *SYNCH* value within country j for each year and use it as our country-level *SYNCH* measure. Similarly, we calculate the equal-weighted variance of the expected value of $r_{i,t}$ ($\sigma^2_{m\,j,t}$) and the equal-weighted variance of $\varepsilon_{i,t}$ ($\sigma^2_{\varepsilon\,j,t}$) as our measures of systematic and firm-specific stock return variation, respectively. To eliminate the impact of exchange rates, we use US dollar-denominated returns to calculate *SYNCH*.

Our second measure of stock price synchronicity is *COMOVE*, the fraction of stocks that move in the same direction in country j. Specifically, we calculate

$$COMOVE = \frac{1}{T}\sum_t \frac{\max\left[n^{up}_{j,t}, n^{down}_{j,t}\right]}{n^{up}_{j,t} + n^{down}_{j,t}}, \tag{2}$$

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where $n_{j,t}^{up}$ is the number of stocks in country j whose prices rise in week t, $n_{j,t}^{down}$ is the number of stocks whose prices fall in week t, and T is the number of weeks used in a given year. The variables *SYNCH* and *COMOVE* each have their own advantages in terms of measuring stock price synchronicity: *SYNCH* considers that different stocks are associated with different levels of market risk (i.e., $\beta_{j,i}$ and $\beta_{us,i}$). In contrast, although we assume that all firms are exposed to the same level of market risk, the estimation procedure of *COMOVE* does not rely on a linear regression model and is therefore not affected by misspecification.

Following Morck et al. (2000), we apply logarithmic transformations of *SYNCH* and *COMOVE*, because these measures are bounded within the interval [0, 1]:

$$LNSYNCH = \ln\frac{SYNCH}{1 - SYNCH}, \tag{3}$$

$$LNCOMOVE = \ln\frac{COMOVE - 0.5}{1 - COMOVE}, \tag{4}$$

3.2 | NRI

Following previous studies (Moeini Gharagozloo et al., 2021, 2022), we use the NRI to measure a country's digitalization level. The NRI measures whether a country has the necessary drivers for digital technologies to unleash their potential and whether these technologies are impacting the economy and society. The NRI was introduced by the World Economic Forum in 2001 and significantly extended in 2012. A high value of the NRI indicates a high level of digitalization.

According to Baller et al. (2016), the NRI sheds light on the level of accessibility and usage of information and communications technology within a country, as well as the impact of digital technologies, given access. The current version of the NRI measures a country's digitalization level in terms of four subindexes, with 10 pillars and 54 individual indicators (Baller et al., 2016). The four subindexes composing digital readiness are the regulatory/business environment, infrastructure, usage, and impact of information and communications technology. Therefore, the NRI is a comprehensive measure of a country's level of digitalization. We use NRI data from the World Economic Forum's database for the period from 2012 to 2016.[9]

3.3 | Control variables

Other factors can lead to cross-country variation in stock price synchronicity. Following Morck et al. (2000), we control for the per capita GDP, macroeconomic volatility, country size, the number of stocks listed, and economic diversification. Specifically, we use the logarithm of the per capita GDP, the variance of the growth of the per capita GDP, the logarithm of the country's geographical size, and the logarithm of the number of stocks listed, and industry- and firm-level concentration as control variables. We use per capita GDP growth within the 3 years before the date of *SYNCH* estimation to calculate the variance of per capita GDP growth. To measure industry- and firm-level concentration, we calculate the Herfindahl–Hirschman index based on the sales of firms and industries, respectively. We identify industries using two-digit Standard Industrial Classification codes.

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To control for the comovement of fundamental earnings, which can also be positively linked to stock price synchronicity, we estimate our earnings comovement measure, which is the R^2 value of the following regression:

$$ROA_{i,t} = a_i + b_{i,t} \times ROA_{j,t} + \varepsilon_{i,t}, \tag{5}$$

where for each firm i at time t, $ROA_{i,t}$ is the return on assets, calculated as annual earnings before interest and taxes over total assets, and $ROA_{j,t}$ is the value-weighted average of the return on assets for all firms in country j. Firms' fundamental data are obtained from Compustat Global.

Previous studies also show that the extent of stock price synchronicity is linked with a country's legal system (Khandaker & Heaney, 2008; Wang & Yu, 2015) and quality of governance (Eun et al., 2015; He et al., 2013; Morck et al., 2000). We include a common law dummy variable that equals one if a country has a UK legal origin and zero otherwise, in our regression specifications.[10] The data for countries' legal origin are obtained from La Porta et al. (2008).[11] To control for the quality of country-level governance, we calculate a good government index, following Eun et al. (2015). Specifically, our good government index is the sum of the percentile ranks of government effectiveness and control of corruption, two indices constructed by Kaufmann et al. (2011).

Finally, motivated by Eun et al. (2015), we control for national culture by including Hofstede's six dimensions of culture (Hofstede, 2001, 1984) in our regression specifications. It is worth noting that Eun et al. (2015) also find that stock price synchronicity is positively associated with national tightness, a dimension of natural culture suggested by Gelfand et al. (2006) and Gelfand et al. (2011). We do not, however, include tightness in our regression specification, because national tightness is covered by Hofstede's six dimensions (Gelfand et al., 2006, 2011; Torelli & Rodas, 2017; Triandis, 2004), and our purpose for including cultural measures is to control for the impacts of national cultures, instead of identifying the effect of cultural dimensions on stock price synchronicity. In addition, a significant portion of our sample is not covered by the data of Gelfand et al. (2011), and including the measure of tightness–looseness in the regression models will significantly shrink our sample size.[12]

3.4 | Sample and empirical design

We collect US stock returns from the CRSP, international stock returns from the Bloomberg Terminal, and NRI data from the World Economic Forum's database. Unlike most international stock price synchronicity research, in our study, the main explanatory variable, the NRI (*NRI*), has both cross-sectional and time-series variations and thus contains more information and more variability than pure cross-sectional data. The macroeconomic data (per capita GDP and geographical size) and firm fundamental data are collected from the World Bank database and Compustat Global, respectively. To mitigate concerns of simultaneity, we use the explanatory variables from the previous year in our regression analysis. Therefore, our sample period for stock price synchronicity is from 2013 to 2017. After excluding observations without valid values for the required variables, our final sample includes 38 countries and 190 observations.[13] To control for the impact of exchange rates, we use the US dollar-denominated values for all the variables.

Panels A and B of Table 1 present the averages of stock price synchronicity and digitalization across countries and the univariate analysis of stock price synchronicity and the

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TABLE 1 Stock price synchronicity and digitalization, by country

Panel A: Stock price synchronicity and digitalization, by country

Country	*SYNCH*	*COMOVE*	NRI	Country	*SYNCH*	*COMOVE*	NRI
Singapore	0.18	0.64	5.97	Ireland	0.15	0.65	5.14
Finland	0.22	0.67	5.96	Malaysia	0.28	0.68	4.84
Sweden	0.26	0.68	5.89	Portugal	0.27	0.68	4.77
Netherlands	0.23	0.68	5.76	Spain	0.27	0.69	4.65
Norway	0.25	0.68	5.71	Chile	0.32	0.80	4.57
Switzerland	0.23	0.67	5.67	Poland	0.24	0.67	4.30
U.S.	0.18	0.65	5.64	Turkey	0.46	0.76	4.28
U.K.	0.18	0.66	5.61	Italy	0.26	0.69	4.25
Denmark	0.21	0.67	5.58	China	0.37	0.73	4.12
Korea	0.22	0.67	5.51	Greece	0.30	0.70	4.00
H.K.	0.15	0.63	5.51	Thailand	0.27	0.69	3.98
Canada	0.23	0.65	5.49	Brazil	0.38	0.71	3.95
Germany	0.19	0.65	5.46	Mexico	0.35	0.71	3.93
Japan	0.23	0.67	5.43	Indonesia	0.22	0.65	3.91
Australia	0.20	0.65	5.38	Philippines	0.18	0.65	3.84
New Zealand	0.28	0.70	5.37	India	0.30	0.69	3.82
Austria	0.28	0.71	5.32	Argentina	0.39	0.70	3.61
Belgium	0.21	0.67	5.19	Pakistan	0.25	0.67	3.34
France	0.19	0.66	5.16	Bangladesh	0.27	0.69	3.25

Panel B: Stock price synchronicity under different levels of digitalization

	High NRI	Middle NRI	Low NRI	High–Low
SYNCH	0.2135	0.2488	0.2995	−0.0860***
COMOVE	0.6646	0.6868	0.6917	−0.0271***
NRI	5.6918	5.0012	3.8441	−1.8477***

Note: Panel A presents the averages of two stock price synchronicity measures (i.e., *SYNCH* and *COMVE*) and *NRI* for 38 countries in our sample. *SYNCH* and *COMVE* are the equal-weighted averaged R^2s estimated from an expanded market model (i.e., Equation 1) and the equal-weighted averaged fraction of stocks that move in the same direction (i.e., Equation 2) in a country. The NRI and its subindices are from Baller et al. (2016). The countries are ranked descending based on their average *NRI*. Panel B presents the averages of *SYNCH, COMVE*, and *NRI* in high-, middle- and low-level of *NRI* and the differences of them between high- and low-level of *NRI*. ***, **, and * indicate that the coefficients are significantly different from zero at the 1%, 5%, and 10% levels.

NRI, respectively. In Panel B, we assign all the country–year observations to terciles based on NRI values and report the averages of *SYNCH*, *COMOVE*, and *NRI* for each tercile and the differences between high- and low-*NRI* terciles.

Our *SYNCH* values are comparable to those reported by Eun et al. (2015) in terms of the cross-sectional pattern. In addition, the overall average of *SYNCH* in this study is lower than

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the value reported by Eun et al. (25% vs. 32%), indicating that the overall level of stock price synchronicity decreases with time (digital development).[14] According to Table 1, generally, countries with low *NRI* levels are associated with high levels of *SYNCH* and *COMOVE*. Specifically, in Panel B of Table 1, the difference in the average *SYNCH* (*COMOVE*) values between high- and low-*NRI* terciles is −0.0860 (−0.0271), statistically significant at 1%. This negative relation between a country's digitalization level and stock price synchronicity is consistent with our prediction, suggesting that high levels of digitalization increase the extent of firm-specific information capitalized into stock prices. Although the univariate analysis results presented in Table 1 show a strong negative correlation between a country's stock price synchronicity and its level of digitalization, this relation could be driven by other factors related to the NRI. To examine the relationship between the NRI and stock price synchronicity in a more sophisticated manner, we run a multivariate analysis controlling for the other factors mentioned in Section 3.1. The descriptive statistics of our key variables are reported in Table 2.

TABLE 2 Summary statistics

Variable	N	Mean	Std Dev	P25	P50	P75
LNSYNCH	190	−1.1285	0.4690	−1.4191	−1.1191	−0.8566
LNCOMVE	190	−0.5781	0.3286	−0.7814	−0.6023	−0.4267
$\ln\sigma_m^2$	190	−7.7232	0.6987	−8.2131	−7.7333	−7.2979
$\ln\sigma_\varepsilon^2$	190	−6.3720	0.4077	−6.6446	−6.3765	−6.0806
NRI	190	4.8465	0.8140	4.0495	5.0767	5.5545
Ln (GDP per capita)	190	9.9177	1.1951	9.2859	10.4522	10.7990
Var (GDP growth)	190	4.1300	12.7169	0.2907	0.7789	3.0255
Ln (Geographical size)	190	12.6924	2.1320	11.4869	12.7320	13.5553
Ln (number of listed firms)	190	5.3908	1.2754	4.5218	5.2756	6.1312
Good Governance Index	190	1.5129	0.4621	1.0914	1.7743	1.9038
Industry concentration	190	0.1388	0.0967	0.0902	0.1173	0.1632
Firm concentration	190	0.0572	0.0643	0.0229	0.0414	0.0640
Earnings' comovement	190	0.2606	0.2487	0.0597	0.1679	0.4152
Power distance	190	54.7368	21.5334	35.0000	58.5000	68.0000
Individualism	190	50.4737	24.5787	26.0000	49.5000	71.0000
Masculinity	190	50.5000	19.4117	42.0000	54.5000	64.0000
Uncertainty avoidance.	190	61.6316	24.7660	44.0000	59.5000	85.0000
Long term normative orientation	190	49.5789	20.6989	33.0000	46.5000	62.0000
Indulgence	190	50.6579	19.8623	38.0000	52.5000	68.0000
Common Law	190	0.3421	0.4757	0.0000	0.0000	1.0000

Note: This table presents summary statistics for the key variables in our sample. The sample consists of country-year observations for 38 countries from 2013 to 2017. The *LNSYNCH* and *LNCOMVE* are the logarithmic transformations of *SYNCH* and *COMVE*. The NRI data are from Baller et al. (2016). See Table A1 in the Online Appendix for the definitions of the other variables.

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To examine the relation between digitalization and stock price synchronicity, we estimate the following regression models, similar to those of Morck et al. (2000):

$$LNSYNCH_{j,t} \quad or \quad LNCOMOVE_{j,t} = \alpha + b\,NRI_{j,t-1} + c\,CONTROLS_{j,t-1} + \varepsilon_{i,t}, \tag{6}$$

$$\ln \sigma^2_{m\,j,t} = \alpha + b\,NRI_{j,t-1} + c\,CONTROLS_{j,t-1} + \varepsilon_{i,t}, \tag{7}$$

$$\ln \sigma^2_{\varepsilon\;j,t} = \alpha + b\,NRI_{j,t-1} + c\,CONTROLS_{j,t-1} + \varepsilon_{i,t}, \tag{8}$$

where *CONTROLS* are the control variables, including the logarithm of the per capita GDP, the variance of per capita GDP growth, the logarithm of a country's geographical size, the logarithm of the number of stocks listed, the good government index, industry- and firm-level concentration, earnings' comovement, Hofstede's six dimensions of culture, and the common law dummy variable. The independent variables are from the previous year. To control for within-country correlations of the residuals, we cluster the standard errors by country.[15]

4 | EMPIRICAL RESULTS

4.1 | Stock price synchronicity and the NRI

We report the results based on Equation (6) in Table 3. Regressions (1) and (4) are our benchmark models, which do not include our key independent variable, *NRI*. In regression (2), which presents our main results, the coefficient of *NRI* is −0.6020 and significant at 1%, indicating that a one standard deviation increase in *NRI* decreases *LNSYNCH* by 1.0448 standard deviations.[16] In addition, adding *NRI* increases the adjusted R^2 value from 0.2934 to 0.3522, an increase of around 20%. Although we control for a variety of country characteristics following previous studies in regression (2), which should largely reflect a country's economic size, economic development, and fundamentals of the economy, there is always a concern of omitted variable bias leading to the endogenous relation between a country's level of development of the digital economy and stock price synchronicity.

To address this concern, in regression (3), we test a regression specification controlling for country-fixed effects but excluding time-invariant variables (geographical size, national culture, and legal system). The results still hold, indicating that our findings are not driven by country-fixed effects. The results based on *LNCOMVE*, presented in regressions (4) to (6), are similar. It is worth noting that, in regression (6), the coefficient of *NRI* is nonsignificantly negative. This could be because *LNCOMVE* only reflects the direction but not the magnitude of stock price movement. Our sample also covers a short period (5 years) and thus largely reflects the cross-country variations of the observations. After controlling for country-fixed effects, we find the relation between a partial measure of stock price synchronicity (i.e., *LNCOMVE*) and the NRI to be weak.

These findings suggest that countries with high digital economy development levels have low levels of stock price synchronicity, supporting H1.

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TABLE 3 Multivariate analysis—stock price synchronicity and digitalization

Dependent variable	*LNSYNCH* (1)	(2)	(3)	*LNCOMVE* (4)	(5)	(6)
Intercept	−2.0627***	−1.0861*	11.2259	−0.0028	0.7625	7.4830*
	(0.7817)	(0.6088)	(7.6813)	(0.8002)	(0.6876)	(3.8515)
NRI		−0.6020***	−0.8415**		−0.4718***	−0.2948
		(0.1290)	(0.3600)		(0.1315)	(0.1987)
Ln (GDP per capita)	0.0589	0.1780*	−0.8169	−0.1445	−0.0512	−0.7044
	(0.0994)	(0.0934)	(0.9484)	(0.1215)	(0.0896)	(0.4891)
Var (GDP growth)	−0.0036	−0.0059***	0.0094	0.0012	−0.0007	0.0086*
	(0.0026)	(0.0021)	(0.0130)	(0.0020)	(0.0015)	(0.0045)
Ln (Geographical size)	0.0809**	0.0675***		0.0421	0.0316	
	(0.0320)	(0.0257)		(0.0292)	(0.0239)	
Ln (Number of listed firms)	−0.0709	−0.0477	−0.2747	−0.0128	0.0053	−0.0403
	(0.0493)	(0.0414)	(0.3062)	(0.0421)	(0.0390)	(0.2003)
Good Governance Index	−0.3008	0.2713	−0.2194	0.2463	0.6946**	−0.2563
	(0.2062)	(0.2243)	(0.9299)	(0.3139)	(0.2965)	(0.4085)
Industry concentration	−0.8058	−0.6490	−0.4335	−0.1172	0.0057	0.6429
	(0.7955)	(0.7180)	(1.2026)	(0.6600)	(0.5964)	(0.8831)
Firm concentration	1.7111	1.1316	−0.0369	0.6438	0.1896	−1.4132
	(1.2397)	(1.0872)	(1.5823)	(0.8539)	(0.7965)	(0.9920)
Earnings' comovement	0.0034	0.1112	0.2557	−0.2216*	−0.1372	0.0780
	(0.1376)	(0.1585)	(0.2379)	(0.1269)	(0.1195)	(0.1456)
Power distance	−0.0005	−0.0019		−0.0034	−0.0046**	
	(0.0026)	(0.0025)		(0.0024)	(0.0023)	
Individualism	−0.0046*	−0.0059**		−0.0046	−0.0057**	
	(0.0027)	(0.0025)		(0.0029)	(0.0025)	
Masculinity	−0.0013	−0.0040***		−0.0008	−0.0029**	
	(0.0017)	(0.0013)		(0.0014)	(0.0013)	
Uncertainty avoidance	0.0025	0.0001		0.0040	0.0021	
	(0.0028)	(0.0026)		(0.0029)	(0.0024)	
Long term normative orientation	0.0031	0.0069***		0.0008	0.0038*	
	(0.0029)	(0.0026)		(0.0025)	(0.0021)	
Indulgence	0.0041**	0.0068***		0.0053*	0.0075***	
	(0.0021)	(0.0015)		(0.0029)	(0.0021)	
Common law	−0.0177	0.0964		−0.1298	−0.0404	

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TABLE 3 (Continued)

	LNSYNCH			*LNCOMVE*		
Dependent variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	(0.1314)	(0.1144)		(0.1146)	(0.0934)	
Observations	190	190	190	190	190	190
Country-fixed effect	No	No	Yes	No	No	Yes
Adj. R^2	0.2934	0.3522	0.5049	0.3097	0.3844	0.6543
F statistic	6.2314***	7.4225***	5.2838***	6.6521***	8.3759***	8.9502***

Note: This table presents the results of regressing the stock price synchronicity on NRI. The dependent variables are *LNSYNCH* and *LNCOMVE*, the logarithmic transformations of *SYNCH* and *COMVE*, respectively. The *NRI* is National Readiness Index from Baller et al. (2016). See Table A1 in the Online Appendix for the definitions of the other variables. Standard errors reported in parentheses are heteroskedasticity robust and are clustered at the country level. ***, **, and * indicate that the coefficients are significantly different from zero at the 1%, 5%, and 10% levels.

4.2 | Effects of the NRI on systematic and firm-specific stock return variations

In this section, we examine the effects of the NRI on systematic and firm-specific stock return variations, respectively, and report the results in Table 4. The dependent variable of regressions (1) and (2) is systematic stock return variation, $\ln\sigma_m^2$. The dependent variable of regressions (3) to (6) is firm-specific stock return variation, $\ln\sigma_\varepsilon^2$. In regressions (2), (4), and (6), we control for country-fixed effects and exclude country-invariant variables (i.e., geographical size, national culture, and legal system).

According to the results of regression (1), the test for H2, the coefficient of *NRI* is −0.7896, significantly negative at 1%, suggesting that countries with high digital economy development levels have low levels of systematic stock return variation. This finding supports H2. The results of regression (2) are similar, indicating that our finding is not driven by country-fixed effects.

In regressions (3) and (4), the coefficient of *NRI* is negative and statistically nonsignificant at 10%, supporting H3. In regression (5), we control for systematic stock return variation by including $\ln\sigma_m^2$ and $NRI \times \ln\sigma_m^2$. The coefficient of *NRI* is 0.7524 and significant at 5%, supporting H4. It is worth noting that, in regression (6), which controls for country-fixed effects, the coefficient of *NRI* is nonsignificant. We argue that this finding should be interpreted carefully and not be considered evidence against the finding in regression (5). Omitted variable bias should not be a serious concern in regression (5), because we have controlled for a variety of country characteristics following previous studies, which largely reflect the size of the economy, the level of its economic development, and its fundamentals. In addition, our sample covers only 5 years and thus largely reflects cross-country variations. Therefore, controlling for country-fixed effects will capture most of the variations (even for the true cross-sectional effects of *NRI*), especially given that the NRI is not expected to change dramatically in a short period. Finally, given that the coefficients of *NRI* are much stabler in regressions (1) and (2) than in regressions (5) and (6), the NRI's effect on stock price synchronicity is mainly driven by its effect on systematic stock return variation, suggesting that the NRI decreases stock price synchronicity mainly through reducing noise trading. In sum, the results presented in this section support H2–H4.

TABLE 4 Regressions of systematic or firm-specific stock return variation on digitalization

	$\ln\sigma_m^2$		$\ln\sigma_\varepsilon^2$			
Dependent variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	−9.6614***	13.8200	−8.7493***	−0.3872	−7.2855***	−4.5202
	(1.2594)	(9.1003)	(1.2003)	(2.3507)	(2.0758)	(3.0108)
NRI	−0.7896***	−1.2575***	−0.0040	−0.1921	0.7524**	0.2598
	(0.2556)	(0.4791)	(0.2387)	(0.1410)	(0.3760)	(0.2702)
NRI × $\ln\sigma_m^2$					0.0616	0.0151
					(0.0477)	(0.0338)
$\ln\sigma_m^2$					0.0858	0.1959
					(0.2495)	(0.1843)
Ln (GDP per capita)	0.5141***	−1.3903	0.3038*	−0.3296	0.1135	0.0329
	(0.1880)	(1.1870)	(0.1685)	(0.2953)	(0.1262)	(0.2653)
Var (GDP growth)	−0.0007	0.0098	0.0005	0.0036	0.0010	0.0013
	(0.0040)	(0.0198)	(0.0034)	(0.0065)	(0.0024)	(0.0036)
Ln (Geographical size)	0.1223***		0.0651		0.0174	
	(0.0368)		(0.0408)		(0.0337)	
Ln (number of listed firms)	0.0463	−0.7758*	0.0859	−0.4609**	0.0733	−0.2515*
	(0.0734)	(0.4280)	(0.0731)	(0.1931)	(0.0528)	(0.1459)
Good Governance Index	−0.3000	−0.0561	−0.5268	−0.0299	−0.4371*	−0.0339
	(0.5210)	(1.1816)	(0.3795)	(0.3417)	(0.2368)	(0.3038)
Industry concentration	−1.7189	−0.6037	−0.5136	−0.1492	0.2568	0.0438
	(1.0848)	(1.3584)	(0.9925)	(0.9252)	(0.7755)	(0.8045)
Firm concentration	3.1605*	0.5736	1.3699	0.6341	0.1222	0.4769
	(1.6346)	(2.1631)	(1.4494)	(1.1632)	(1.1010)	(0.8417)
Earnings' comovement	0.3499*	0.1977	0.0096	−0.1488	−0.1095	−0.2037**
	(0.1933)	(0.2798)	(0.1939)	(0.0944)	(0.1606)	(0.0918)
Power distance	−0.0012		0.0007		0.0008	
	(0.0042)		(0.0045)		(0.0034)	
Individualism	−0.0069		−0.0020		0.0007	
	(0.0045)		(0.0032)		(0.0023)	
Masculinity	−0.0063***		−0.0008		0.0014	
	(0.0023)		(0.0024)		(0.0017)	
Uncertainty avoidance	−0.0024		−0.0023		−0.0015	
	(0.0034)		(0.0029)		(0.0025)	

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TABLE 4 (Continued)

Dependent variable	$\ln\sigma_m^2$ (1)	(2)	$\ln\sigma_\varepsilon^2$ (3)	(4)	(5)	(6)
Long term normative orientation	0.0054		−0.0052		−0.0069**	
	(0.0035)		(0.0035)		(0.0029)	
Indulgence	−0.0036		−0.0125***		−0.0108***	
	(0.0043)		(0.0040)		(0.0026)	
Common law	0.2364**		0.0621		−0.0300	
	(0.1146)		(0.1674)		(0.1367)	
Country-fixed effect	No	Yes	No	Yes	No	Yes
Observations	190	190	190	190	190	190
Adj. R^2	0.3944	0.5542	0.3807	0.7925	0.6252	0.8847
F Statistic	8.6944***	6.2205***	8.2610***	17.0432***	18.5184***	31.8514***

Note: This table presents the results of regressing the systematic or firm-specific stock return variation on NRI. The dependent variables are $\ln\sigma_m^2$ (regressions 1 to 2) and $\ln\sigma_s^2$ (regressions 3 to 6), the logarithmic transformations of systematic and firm-specific stock return variations, respectively. The *NRI* is National Readiness Index from Baller et al. (2016). See Table A1 in the Online Appendix for the definitions of the other variables. Standard errors reported in parentheses are heteroskedasticity robust and are clustered at the country level. ***, **, and * indicate that the coefficients are significantly different from zero at the 1%, 5%, and 10% levels.

5 | CONCLUSION

In this study, we document that a high level of digital economy development reduces the extent to which stock prices move together (i.e., stock price synchronicity), suggesting that high development levels of the digital economy elevate the amount of firm-specific information capitalized into stock prices. Our results also indicate that high digital economy development levels decrease stock price synchronicity by reducing systematic stock return variation, a manifestation of noise trading. Finally, we show that the digital economy development level has no significant effect on firm-specific stock return variation, a factor related to both noise trading and firm-specific information incorporated into stock prices, and this effect becomes positive after we control for levels of noise trading (i.e., systematic stock return variation).

This study sheds light on the extent to which stock prices will move together and the drivers behind their variation. Given that digitalization is expected to continue to increase around the world, our findings suggest that the declining trend of stock price synchronicity will persist and expand from developed to developing countries. Furthermore, by linking stock price synchronicity and its two components to the level of digital economy development—a factor reducing the complexity and costs of information production, collection, transmission, and analysis—we find evidence to support the view that stock price synchronicity is negatively related to the capitalization of firm-specific information into stock prices. Additionally, our findings back the view that systematic stock return variation reflects the level of noise trading. Finally, consistent with previous studies, our findings suggest that firm-specific stock return variation is driven by both the firm-specific information capitalized into stock prices and the level of noise trading, but its link to noise trading is weakened after controlling for systematic stock return variation.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are not shared because the paper makes use of the proprietary data, including CRSP, Bloomberg Terminal, and Compustat.

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ENDNOTES

[1] According to the definition developed by the Bureau of Economic Analysis, the digital economy includes (1) the digital infrastructure needed to enable the existence and operation of computer networks, (2) the digital transactions that take place using that system, and (3) the content that digital economy users create and access (Barefoot et al., 2018). Similarly, MATEC Web of Conferences defines digital economy as a kind of economy characterized by the active implementation and application of digital technologies for the collection, storage, processing, transformation, and transmission of data in all areas of human activity (Borremans et al., 2018).

[2] Academic studies must use publicly announced information, which, according to signalling theory (e.g., Leland & Pyle, 1977; Spence, 1978), can be subject to firm managers' expectations about firms' stock price informativeness.

[3] We provide a detailed hypothesis development in Section 2.

[4] According to literature (Aabo et al., 2017; Morck et al., 2000), a high level of noise trading generates a high level of systematic stock return variation that is unrelated to the movements of fundamentals in economies.

[5] See Section 3 and Table A1 in the Online Appendix for the definitions of the variables.

[6] See Tables A2 and A3 in the Online Appendix for the correlations between the variables and the results of these tests.

[7] For example, Wurgler (2000) shows that firms with lower stock price synchronicity invest more efficiently. Chen and Doukas (2022) find that stock price synchronicity boosts the profitability of momentum strategy by amplifying investor underreaction to information. F. Dong and Wilson (2019) find that mutual fund profitability and the importance of fund managers' skill are sensitive to the level of stock price synchronicity.

[8] Conventional financial economics assume the participants in the financial market are homogeneous in terms of skills, such that they generate the same beliefs if they receive the same information. However, recent studies show that the investment skills of market participants are heterogeneous (e.g., Bai et al., 2021; Kacperczyk et al., 2014; Kacperczyk & Seru, 2007). Therefore, new private information can be generated from existing public information if the participants do not publicly share their beliefs.

[9] See http://www3.weforum.org/docs/GITR2016/WEF_NRI_2012-2016_Historical_Dataset.xlsxforthedata.

[10] Our results also hold when we control for UK, French, German, Scandinavian, and socialist legal origins.

[11] See https://faculty.tuck.dartmouth.edu/rafael-laporta/research-publications for the legal origin data.

[12] We also examine the effects of NRI while controlling for tightness–looseness in a subsample. The results still hold.

[13] The research data used in this study cannot be publicly shared, since they were obtained from licensed portals and any data sharing would compromise legal requirements. The data supporting the empirical

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findings of this study can be obtained from Compustat Global, the CRSP, and the Bloomberg Terminal. Restrictions apply to the availability of data obtained under license.

[14] See Table A4 in the Online Appendix for the detailed comparison.

[15] We do not cluster standard errors by year, because there are only 5 years of data, which would induce a small cluster problem and bias the standard error estimates (Cameron et al., 2008).

[16] The calculation is as follows: $-0.6020 \times 0.8140/0.4690 = 1.0448$.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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