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# Cloud economy and its relationship with China's economy—a capital market-based approach

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**Abstract**

Through the lens of the stock market, we examine whether and how the cloud economy affects China's economy. We review the literature on cloud computing and related concepts and propose a definition of the cloud economy. Based on this new definition, we create a China Cloud Economy Index (CCEI) and its sub-indices. Using stock market data from 2012 to 2020, we analyze the basic characteristics of these indices, their validity, and their relationship with the overall stock market. The robustness of the new index is also examined. We find that the relationship between the CCEI and the stock market had been getting stronger but weakened somewhat after January 11, 2019 plausibly because of the availability of recent cloud-related policies that have widened the gap between the market performance of CCEI and that of the stock market.

**Keywords:** Cloud economy, Cloud index, Stock market, China

**JEL Classification:** G20, G10, O16

## Introduction

Cloud technology is one of the globally recognized emerging technologies in the new millennium that are most likely to change people's lives. As quoted in Thornburg (2009), "Cloud Computing" was first proposed by John Gage who envisaged that "the network is the computer." Precisely, cloud infrastructure comprises server hardware, network equipment, storage systems, and proprietary software (Bayrak et al. 2011), which is designed to help companies to build an accessible program with their infrastructure through web services (SDX Central 2011) to promote software product upgrading (Alarcon and Pavlou, 2017). In 2006, Amazon launched the Elastic Compute Cloud Service, which marked the start of the cloud business model. In August of the same year, Eric Schmidt, CEO of Google, formally introduced the concept of "cloud computing" at the Search Engine Strategies Conference and Expo and announced in 2007 that Google would cooperate with IBM in the field of cloud technology in 2007. Since then, tech giants have flocked to the cloud industry. In the next four years, the development of the cloud computing industry in developed countries accelerated (Lu and Zhang 2020), and the world entered a new era—the cloud economy.

As an emerging general technology, cloud computing poses a great challenge to the concepts and practices of traditional computing technology (Coyle and Nguyen 2020). For example, a centralized data center can use a public cloud platform to provide citizens with sufficient public and innovative services (Kaminsky et al. 2020). Thus, using cloud computing, organizations can take advantage of economies of scale to innovate efficiently and quickly (Gkika et al. 2020). Although it is an emerging concept and industry, the economic benefits of the cloud are obvious. The great prospect of the cloud industry is its potential to accelerate and promote the new model of information and communications technologies (ICTs)-driven economic growth (Iansiti and Richards 2012).

SAP (2012) pointed out three factors that underline the success of the development of the cloud economy, including the cloud economy ecosystem, the new business environment and business development model, and a vision to help small and medium-sized enterprises out of technical bottlenecks and assist large enterprises in integrating technical standards. Coincidentally, at the 4th Annual American Business Research Conference in New York, from a financial perspective, Yamin and Tsaramirsis (2012) proposed a concept of cloud economy characterized by infrastructure, systems, and services. The cloud has the advantage of "enhancing the financing capacity of enterprises with little capital funding." There is no doubt that it has made an outstanding economic contribution to modern ICT and played an important role in its development (Riley et al. 2017). The cloud can help enterprises to strengthen their longevity and resilience by reducing operating costs and enhancing flexibility in strategic decisions (Etro 2011).

Jin and McElheran (2019) pointed out that, unlike previous technological revolutions, key features of the cloud are particularly useful for firms facing high uncertainty (such as young firms) because a key ability of the cloud is to pool resources across a wide range of firms to obtain shared economies of scale in IT services, providing these firms with more flexible IT solutions at lower upfront or average costs. In addition, this flexibility allows these firms to try different types of IT solutions with much shorter learning curves and lead times, thus significantly reducing trial and error costs. Cloud computing and its related IT services equip these firms with a means to achieve better performance before gaining their own experience and scale. In addition, manufacturing enterprises can benefit from cloud-based sales and marketing, enterprise resource planning, supply chain management, and payment. They increasingly rely on bundled IT services for data collection, storage, analysis, and communication. Despite many benefits, Jin and McElheran (2019) also discussed some limitations of the development and promotion of cloud-based IT services. These limitations include the following. (1) IT solutions are usually very standardized and may not be suitable for important core business functions within a firm. (2) Data security is always a concern. For example, firms may lose control over their data or software upgrade plans if it outsources IT solutions on the cloud (Rashid 2016). (3) Unpredictable and uncontrollable downtime of IT solutions are other issues that cannot be overlooked (Weise 2017). (4) Finally, the unit costs of the cloud may be not competitive when compared with the cost of setting up a data center for personal use (Metz 2016). To a large extent, the cloud has become a positive force for transformation in technology, business, and beyond (Hooton 2020), and applications of the cloud are almost everywhere. Although people find it difficult to track its footprint accurately, it does not prevent the arrival of the third industrial civilization, bringing about a complete overturn of previous norms of human existence.

In the past, researchers focused primarily on using cloud technology to enhance business operation efficiency and promote the digitalization of the market to improve public order. Their research was about the development and use of cloud technology. Few scholars have realized the importance of understanding the cloud economy from a valuation perspective; research that has studied the macro-implications of the cloud economy is rare. Although there is an increasingly closer relationship between enterprises and cloud activities, little attention has been paid to measuring the development of the cloud enterprise market and how it is related to the economy. In addition, existing research about the cloud economy is based primarily on developed countries rather than emerging markets (Joia and Marchisotti 2020). Most scholars have studied and explained only the definition and utility of cloud computing but have rarely summarized the economic value of the cloud.

Anecdotal evidence (such as cloud-related news, reports, and policies issued by domestic or foreign research institutions or government agencies) suggests that the cloud economy has grown gradually (see some examples in “Appendix”). Therefore, a systematic study of the development of the cloud economy and how it is related to the economy, especially in China, is needed.

Using China—the largest emerging market in the world—as the object of this study, we aim to describe and quantify the relationship between the cloud economy and its economy. To understand the relationship between the cloud and the macro-economy effectively and to quantify the substantial contribution of the development of the cloud economy, we first compare the concepts related to the cloud economy, briefly analyze the application of the cloud economy, and propose a reasonable definition. Based on this definition, we construct a China Cloud Economy Index (CCEI) and use this index as a proxy for the cloud economy in China. Using the stock market as a lens to capture the economy, we analyze how the CCEI (as a proxy for the cloud economy) is related to the stock market (as a proxy for the economy).

The rest of this paper proceeds as follows. "Literature review" section reviews the relevant literature and develops hypotheses. "CCEI" section outlines the design and details of CCEI. "Market performance of CCEI" and "Robustness check of the alternative measure of CCEI" sections present the empirical results and robustness check results, respectively. The conclusions are discussed in "Conclusion" section.

## Literature review

### Basic concepts and definitions of cloud computing and cloud economy

Existing studies have examined cloud computing mainly from business and technical perspectives. For example, IBM (2013) mentioned in its white paper that “cloud computing is described as a computing platform or a type of application, which has both physical and virtual properties and can be dynamically adjusted at any time as required.” The content of the cloud computing service that is found by the previous researchers include the following aspects. (1) Merging Internet base service resources and (2) assisting users instead of self-developing or participating in project research and development (Liu 2017). Thus, it is a new technology that is jointly promoted and gradually developed by cloud service providers and is expected to lead the process of global digitalization.

However, the term cloud computing may not be good enough to explain all the types of enterprises that support its whole industrial/supply chain because some entities are probably not directly involved in the research and development of cloud computing but have benefited from the development of cloud computing technology. The economic benefits of the peripheral industrial chain related to cloud computing are far beyond the total economic output of several giant cloud service providers. Therefore, due to the rapid development of the cloud economy, whose impact needs to be assessed, a definition of the cloud economy is needed to fill the gap in the literature. We now review studies that have defined or measured related concepts of cloud economy.

Few studies have defined or measured the high-technology sector or digital economy (CompTIA 2021; Hooton 2018; Barefoot et al. 2018). Hooton (2018) discussed some theoretical features that characterize the technology intensity of a high-technology sector and provided a succinct review of several approaches to defining the high-technology sector. These features are R&D investment, the number of STEM employees, as well as the complexity and novelty in production and product/service. The first two features are sometimes called input-based criteria, whereas the last two are called output-based criteria (Heckler 2005). These approaches also differ from each other in terms of whether they are defined/included at the industry level and the number of the features that are defined/included at the industry level (Cortright and Mayer 2001; Chapple et al. 2004; Heckler 2005; CompTIA 2021), firm level (O'Regan et al. 2008; Kile and Phillips 2009), or product/service level (Steenhuis and de Bruijn 2006). He also proposed a continuum-based approach to identify technology intensity in industries, businesses, and products/services. For example, CompTIA (2021) defined the technology industry as firms that are "involved in making, creating, enabling, integrating, or supporting technology, whether as a product or service." Similarly, Barefoot et al. (2018) discussed the Bureau of Economic Analysis (BEA) approach of operationally defining and measuring the digital economy. According to BEA, the digital economy is primarily defined in terms of the Internet and related ICT and other sectors, including digital enabling infrastructure, e-commerce, and digital media. They applied this definition to identify relevant goods and services and the supply-use framework of BEA to determine the industries that produce these goods and services.

In China, the G20 Hangzhou Summit 2016 outlined the definition of "digital economy" in the G20 Digital Economy Development and Cooperation Initiative. Digital economy refers to a series of economic activities where digital knowledge and information are regarded as key productivity factors; the modern information network is an important activity space, and ICT is utilized as an important driving force for productivity growth and economic structural optimization.

These conceptual and operational definitions of the digital economy or high-technology sector are useful because they provide different perspectives based on which the cloud economy can be defined. Compared with the digital economy or high-technology industry, the cloud economy is different in the following ways:

1. Cloud economy is not limited to the "core" features of the "technology" economy proposed by Hooton (2018) because it also refers to all non-contact economic behaviors and facilities required to maintain such economic behaviors.
2. The areas covered by the cloud economy include not only all technology industries proposed by CompTIA (2021) but also the upstream and downstream industries in the supply chain of the whole technology industry. For example, smart grid operation enterprises are upstream power service providers of technology industries, whereas cultural media enterprises are downstream industries of technology enterprises.
3. Similar to BEA's operational definition, cloud economy also emphasizes digital media, but it has much wider applications in scope than the digital economy proposed by BEA. For example, payment technology and the Internet celebrity economy are extensions of the digital economy.

In view of the above discussion, we propose the following definition: "cloud economy is a series of contactless economic activities with technological research or commercial interaction as the key factor for production and mobile terminals or interactive digital devices as the major medium of information dissemination."

Our definition of the cloud economy is similar to that of the G20 Hangzhou Summit in 2016, but they are different. In particular, the digital economy definition emphasizes the technologies on which the digital economy is based, viewing optimization of the economic structure and improving operational efficiency as the main driving forces. However, the definition of the cloud economy pays more attention to the domains/fields wherein cloud technologies can be applied.

**Valuation of the cloud economy**

The cloud economy is in the early stages of development, and professionals in emerging countries have not fully realized its strategic value and the new business models it might create (Joia and Marchisotti 2020). In academia, research on the value of the cloud is very rare and is mostly in the exploration stage. For example, Kash et al. (2019) examined the problem of cloud pricing and proposed that the ratio of server parameter settings can be improved to boost profits and revenue. Jain and Hazra (2018) discussed the impact of the buyers' market-demand correlation, load conditions of demand, and other factors on the cloud capacity portfolio decision. Lee (2019) proposed a pricing model of cloud service and constructed a decision-making model designed to maximize profits based on the perspectives of both cloud providers and customers. Compared with technological innovation and development research in the traditional business or financial field, such as the application of opinion dynamic models (Zha et al. 2020) and financial data clustering methods (Li et al. 2021), research on the value of the cloud economy is scant.

Hooton (2020) and the European Commission (2020) applied different methods to study the impact of cloud computing on the economy. The former illustrated the role of the cloud in the U.S. economy by identifying statistics on specific receipts in the product lines of cloud-related industries in NAICS. The author estimated the economic contribution of cloud computing to output, income, employment, value creation, direct-effect earning, and direct-effect employment, pointing out that Computer System Design

Services (NAICS code: 541512) and Custom Computer Programming Services (NAICS code: 541511) have made the greatest contribution to cloud computing, and Data Processing, Hosting, and Related Services (NAICS code: 518210) has become the largest beneficiary in the development of cloud computing. Unfortunately, the author has not been able to classify different types of cloud economies according to different statistical calibers. Therefore, there is no way to determine whether the extent of the impact of the cloud on enterprises would vary in different types of enterprises or would be influenced by individual differences. Moreover, the problem of using quarterly or annual data in the analysis will likely limit its usefulness in the decision-making context because of time-lagging issues. Subsequently, the European Commission (2020) applied a method of simulation to deduce the potential economic benefits of the cloud economy. By varying the set of parameters in the simulation model, the author deduced different scenarios and tried to provide valuable feedback for policymakers. However, the usefulness of the scenario analysis mainly depends on the validity of the model deduction, making the conjecture not always convincing. By comparison, the CCEI proposed in this study is designed and based on real-time stock market data. Therefore, its relationship with the stock market is largely driven by these data and an ordinary least squares (OLS) model with minimal but reasonable assumptions. Thus, any prediction that is based on this empirical relationship is expected to be reasonably accurate. This approach is also versatile because as stock market data are rich, one may use them at different frequency levels (e.g., monthly, weekly, daily, or even higher frequencies). In addition, the validity of the quantitative model can be checked by back-testing with historical data. In short, our approach provides researchers/decision-makers with an alternative suitable tool for understanding the market value of the cloud economy.

## CCEI

### Construct design of CCEI

Academia has never stopped studying innovative economic activities. After determining the limitations of the neoclassical growth model, Romer (1986) and Lucas (1988) proposed the new growth theory, using endogenous technology to explain economic growth. At the enterprise level, economic growth can be roughly attributed to two factors—acquiring and applying new knowledge in production. The former is one of the most prominent points of view in the new growth theory, whereas the latter is implicit in various models and is the premise of market conditions, property rights, and economic stability faced by enterprises. Coincidentally, Schumpeter (1911) suggested that in the process of multi-entity participation and multi-factor interaction, the interaction between technological progress and the actualization of innovation promotes technological innovation. Technological progress and the actualization of innovation can be regarded as a pair of "double-helix structures" (innovative double-helix theory), with harmony existing in diversity moving hand in hand. The former refers to the accumulation and improvement of technology-related knowledge, whereas the latter is committed to building a smooth and efficient innovation service system to provide technology and product research and development with information closest to the market and user needs to achieve application innovation.

The cloud economy may be viewed as an innovative behavior in the process of modern social and economic development. Therefore, cloud economic activity should be an economic behavior characterized by innovation. Based on the new definition of the cloud economy theory mentioned earlier, we construct the CCEI to provide users with effective measurement of the developmental level of the cloud economy. Referring to the new growth theory and the innovative double-helix theory, we divide all cloud economic activities into two aspects—one is technology, and the other is application. The former aims to provide necessary technical support (technology cloud) for the development of the cloud economy, and the latter provides suitable application fields/domains (including online cloud, financial cloud, platform cloud, and city cloud) for the promotion/application of cloud technology.

We first define five first-tier indices/groups in terms of their distinctive features. For example, for the technology cloud index/group, three distinctive features are identified, and they are (1) the firm uses the Internet as a carrier; (2) the firm provides technical support for the cloud economy; and (3) the firm views technology research, development, and production as its main business (see Column (2) of Table 1 for the features of other first-tier indices). We check whether a particular firm can meet these features. If it can, it becomes part of this group/index. According to RoyalFlush, there are 535 subgroups in the Chinese stock markets. For these five indices, out of 535 indices from RoyalFlush, we select 62 s-tier indices that meet the definitions of the first-tier indices (see Column (2) of Table 1). The number of listed firms related to the cloud economy is huge and ever-increasing. Not all of these firms outperform the A-share market. Grouping all these firms into five subgroups may help investors to identify the five groups/dimensions of the cloud economy that is/are performing better. Therefore, their indices or indicators may shed light on this issue. Due to the lack of space, the details of the constituent stocks of each sub-index will not be elaborated (please consult Hithink RoyalFlush Information Network Co., Ltd. at http://www.51ifind.com for more information).

Some enterprises may be involved in more than one of the first-tier indices. Figure 1 illustrates such a possibility. As an illustration, Fig. 1 cites only nine enterprises to reveal the mapping relationships among first- and second-tier indices, listed companies, and CCEI. For example, the second-tier index A comprises enterprises a, b, and d, where a or b is one of the constituent stocks of index A, while d is not only a component of index A but also part of index B, and it also combines index C with e. Although constituent stocks may belong to more than one secondary index, a second-tier index corresponds to only one first-tier index. For example, indices A, B, and C belong only to index T, and indices D and E belong only to index F.

## Data source and criteria for sample selection

Our valuation approach is rooted in the premise that stock prices can reflect market value. Due to the reliability and accessibility of high-quality stock price data, we select the daily closing price of the China A-shares market as the source data of CCEI. Because the prevalent herd effect in the capital market may affect rational market evaluation

**Table 1** The evaluation system of CCEI

| First-tier indices | Definitions of first-tier indices | Second-tier indices |
|---|---|---|
| Technology Cloud Index (TCI) | 1. Internet as a carrier<br>2. Provide necessary technical support for cloud economy<br>3. Technology research and development and production as the main business | Mobile Payments [885333], Cloud Computing [885362], Big data [885452], Network Security [885459], Robotics [885517], 3D Printing [885537], 5G [885556], Satellite Navigation [885574], Virtual Reality [885709], Artificial Intelligence [885728], Quantum Communications [885730], Automatic Pilot [885736], Blockchain [885757], Facial Recognition [885759], Smart Speaker [885771], Speech Technology [885772], Industrial Internet [885783], Edge Computing [885790], Digital Twins [885820], RCS [885889] |
| City Cloud Index (CCI) | 1. Internet as a carrier<br>2. Closely related to the daily life of urban and rural residents<br>3. Directly or indirectly involved in the process of urbanization construction | Smart Grid [885311], Internet of Things [885312], Smart City [885378], Smart Healthcare [885402], Drones [885564], Internet of Vehicles [885662], Online Car-hailing [885753], WeChat Mini Program [885754], Internet Healthcare [885765], Intelligent Transportation System [885766], Auto Retail [885768], Intelligent Logistics [885770], Internet of Things in Power Systems [885819], ETC [885861], Data Center [885887] |
| Platform Cloud Index (PCI) | 1. Internet as a carrier<br>2. Including local cloud computing enterprises or other companies having direct business contacts with them<br>3.Provide Internet finance and other services for third parties | Apple Concepts [885376], Alibaba Concepts [885611], Ant Group Concepts [885749], Tencent Concepts [885779], Xiaomi Concepts [885785], Baidu Concepts [885797], Huawei Concepts [885806] |
| Online Cloud Index (OCI) | 1. Internet as a carrier<br>2. Provide online services for third parties (Cultural, educational, entertainment services and etc., excluding Internet financial services)<br>3. Internet services as the main business | Culture media [885418], Online Education [885480], Online Tourism [885497], Webcast [885788], Mobile Games [885457], Online Games [885603], E-Sports [885737], Cloud Games [885874], Internet Celebrity Economy [885876], Cloud Office [885881] |
| Financial Cloud Index (FCI) | 1. Internet as a carrier<br>2. Not a local famous cloud computing enterprise<br>3. No direct business dealing with domestic famous cloud computing enterprises<br>4. Provide Internet financial services for third parties | E-commerce [885420], Internet finance [885456], Rural E-commerce [885629], Cross-border E-commerce [885642], Internet Lottery [885647], Medical E-commerce [885661], Digital Currency [885866], Internet Insurance [885767], New Retail [885784], C2M Concepts [885888] |

First-level indices and their definitions are developed by the authors and are used to identify the second-tier indices from the concepts stock of the RoyalFlush iFinD Index on August 31, 2020. The column of second tier indices shows the key words and search codes [in square brackets] they use to identify the second-tier indices. Readers can use the codes to obtain the corresponding stock data in RoyalFlush iFinD database. It should be noted that the number of stocks under each conceptual category may change over time. The data involved in CCEI is taken from August 31, 2021. If readers are interested, we can provide all the search codes of RoyalFlush iFinD as of August 31, 2021

adversely, we minimize the impact of speculative trading on stock prices by lengthening the period and reducing the sampling frequency. Therefore, the sampling interval is weekly, and the period is from January 1, 2012 to August 31, 2020. All the second-tier indices and stock price data come from the RoyalFlush iFinD financial data platform.

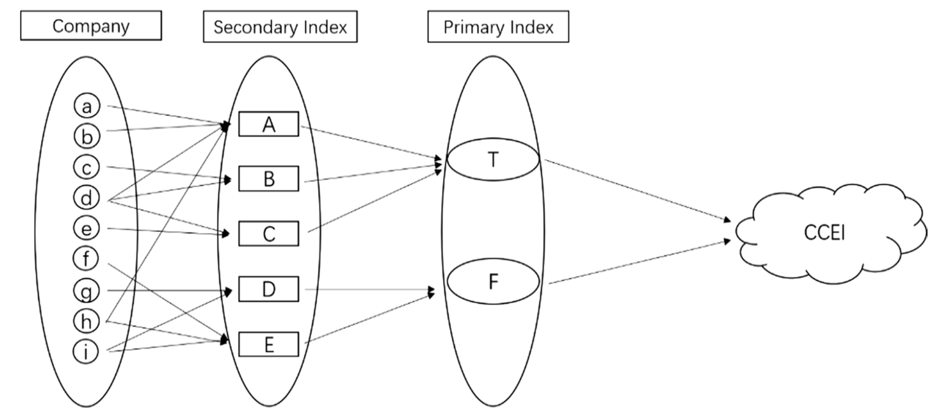


**Fig. 1** Mapping relationship between CCEI and its sub indicators to listed enterprises. *Note* T and F refer to 2 First-level indices, A–E refer to 5 s-tier indices, and a–i refer to 9 enterprises

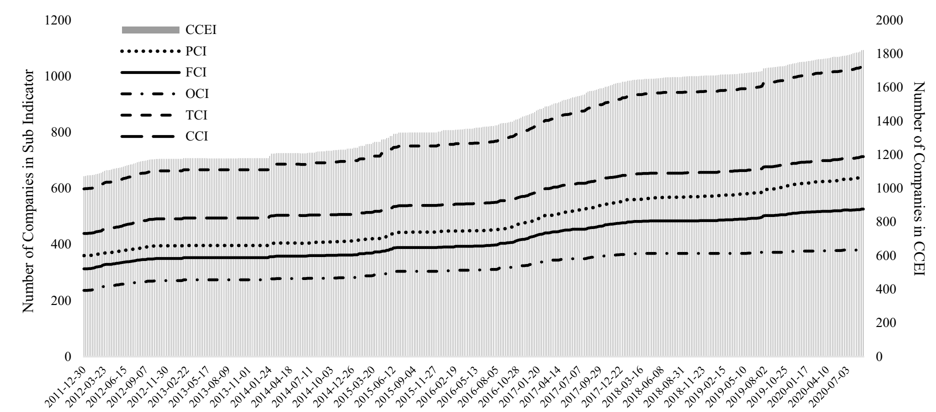


**Fig. 2** The Proportion of CCEI and its Sub-Index Enterprises in the whole industry. *Note* The statistical results are based on RoyalFlush iFinD Index as of August 31, 2020

## Methodology of CCEI compilation

To construct CCEI, we use the weighted average method. This method is relatively simple to use and completely consistent with international practices of index compilation without causing market shocks and leverage effects (Li and Jiang 2002; Xu et al. 2020). The formula is as follows:

$$D_i = \sum_{i=1}^{n} w_{i,t} * P_{i,t}$$

where $D$ refers to the weekly value of CCEI; $w$ represents weight; $w_{i,t} = \frac{m_{i,t}}{\sum_{i=1}^{n} m_{i,t}}$; $P$ represents weekly closing price; $m$ represents weekly market capitalization of stocks in circulation of company $i$; $i$ denotes company $i$; $t$ denotes week $t$.

The number of companies covered by CCEI and its sub-indices are not invariable over time. We track the number of listed companies on a real-time basis, and the results are depicted in Fig. 2.

**Table 2** CCEI component stocks by GICs

| Sector | Project | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | PCI | OCI | TCI | CCI | FCI | CLC | NCLC | TCW | PCW |
| Communication Services | 50 | 121 | 70 | 28 | 28 | 130 | 2 | 132 | 98.48% |
| Information Technology | 347 | 100 | 509 | 354 | 110 | 646 | 158 | 804 | 80.35% |
| Consumer Discretionary | 73 | 80 | 109 | 57 | 157 | 285 | 283 | 568 | 50.18% |
| Industrials | 82 | 32 | 233 | 192 | 68 | 403 | 554 | 957 | 42.11% |
| Consumer Staples | 13 | 17 | 12 | 12 | 71 | 88 | 155 | 243 | 36.21% |
| Real Estate | 7 | 13 | 13 | 9 | 18 | 42 | 97 | 139 | 30.22% |
| Financials | 8 | 0 | 9 | 0 | 15 | 25 | 86 | 111 | 22.52% |
| Materials | 48 | 16 | 70 | 23 | 37 | 143 | 508 | 651 | 21.97% |
| Healthcare | 10 | 2 | 11 | 34 | 17 | 57 | 278 | 335 | 17.01% |
| Utilities | 4 | 0 | 3 | 5 | 4 | 13 | 94 | 107 | 12.15% |
| Energy | 1 | 0 | 3 | 3 | 4 | 7 | 79 | 86 | 8.14% |
| Total | 643 | 381 | 1042 | 717 | 529 | 1839 | 2294 | 4133 | 44.50% |

*CLC* The number of cloud economy listed companies. *NCLC* The number of non-cloud economy listed companies. *TCW* The total number of Listed Companies in the whole industry; as some individual companies may fall into more than one categories, we do not simply add the industry classification items. *PCW* The proportion of cloud listed companies in the whole industry

### CCEI industry classification standard

To some extent, the industries to which CCEI constituent stocks belong embody or reflect the industry attributes of the development of the cloud economy. We classify 1,839 listed companies selected from the CCEI, including five first-tier indices and 62 s-tier indices, according to the Global Industry Classification Standard (GICS). Table 2 reveals that among the CCEI constituent stocks, the total number of enterprises in Information Technology, Industrials, and Consumer Discretionary accounts for a commanding share of over 70%. In terms of industry coverage, both Telecommunication Services and Information Technology are the most important industries in the process of cloud economic development, accounting for 98.48% and 80.35% of the overall market share, respectively. They are closely followed by Consumer Discretionary and Consumer Staples and Industrials. The first two industries are important supply and marketing channels for promoting the development of the cloud economy, and the latter provides the necessary technical support for the development of the cloud economy. The coverage rates of Consumer Discretionary and Consumer Staples and Industrials are 50.18%, 36.21%, and 42.11%, respectively. Next, real estate is an important pillar of China's economy, which had contributed 7.39% to China's GDP by the end of the first quarter of 2020. However, it is not easy for large real estate companies to succeed in digital transformation. It is estimated that only 42 out of the 139 real estate companies that are publicly listed in China's securities market are involved in the cloud economy, suggesting that the tie between real estate companies and the cloud economy is not strong. Moreover, the Financials (banks, securities dealers, insurance companies, etc.) has always lagged behind in the development of digital technology. The scientific and technological development of China's financial enterprises is rather stagnant, where the industry coverage of cloud technology is less than a quarter of the overall market. Although the Financials accounts for a high proportion of the national economy, insurmountable barriers

**Table 3** Spearman rank correlation test

| Panel A | CCEI | PKU-DFIIC | Panel B | CCEI | CHIT |
|---|---|---|---|---|---|
| CCEI | 1.000 | 0.786 | CCEI | 1.000 | 0.796 |
| PKU-DFIIC | 0.786 | 1.000 | CHIT | 0.796 | 1.000 |

Panel A result is based on annual data from 2013 to 2018. Panel B result is based on monthly data from January 2012 to December 2020

**Table 4** Result of Spearman rank correlation test

| | OCI | PCI | FCI | TCI | CCI |
|---|---|---|---|---|---|
| OCI | 1.000 | 0.898 | 0.535 | 0.861 | 0.886 |
| PCI | 0.898 | 1.000 | 0.784 | 0.977 | 0.977 |
| FCI | 0.535 | 0.784 | 1.000 | 0.840 | 0.794 |
| TCI | 0.861 | 0.977 | 0.840 | 1.000 | 0.993 |
| CCI | 0.886 | 0.977 | 0.794 | 0.993 | 1.000 |

From January 1, 2012, to August 31, 2020, with weekly data

to entry and minimalist business models to ensure stable yields in the financial industry have been major drawbacks to financial innovation.

#### Construct validity of CCEI

Several tests are used to examine the construct validity of CCEI. First, we examine the correlation of CCEI to other similar indices in the literature. These indices are the Global X MSCI China Information Technology ETF (CHIT) and the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC). CHIT is based on the methodology of the MSCI Global Investable Market Index, and it includes all eligible securities related to information technology, which is the epitome of China's listed information technology companies. Therefore, it may be used as the benchmark to measure the overall development of China's listed information technology companies. As Spearman rank correlation is less sensitive to outliers, we employ it in this study (see Table 3). The Spearman correlation between CHIT and CCEI is 0.796 and statistically significant at the 1% level, indicating that CCEI is consistent with CHIT in the sense that CCEI is as valid as CHIT in capturing the degree of technological development in China. Produced by the Institute of Digital Finance at Peking University, PKU-DFIIC is a set of digital financial inclusion indices, which quantitatively illustrate the situation of China's innovative Internet finance. The Spearman correlation coefficient between PKU-DFIIC and CCEI is 0.786 and statistically significant at the 5% level, indicating that there is also a strong correlation between them. Both results reveal that the proposed index is reliable.

#### Correlation analysis of CCEI sub-indices

To test the internal consistency of the CCEI indices, we estimate the correlation between the five first-tier indices, and the results are presented in Table 4. As presented in Table 4, the correlation coefficients among the indices are relatively high, ranging from 0.535 to 0.993. These indices may overlap with each other because some listed companies may be constituent stock of more than one index as it is rare for a listed company to

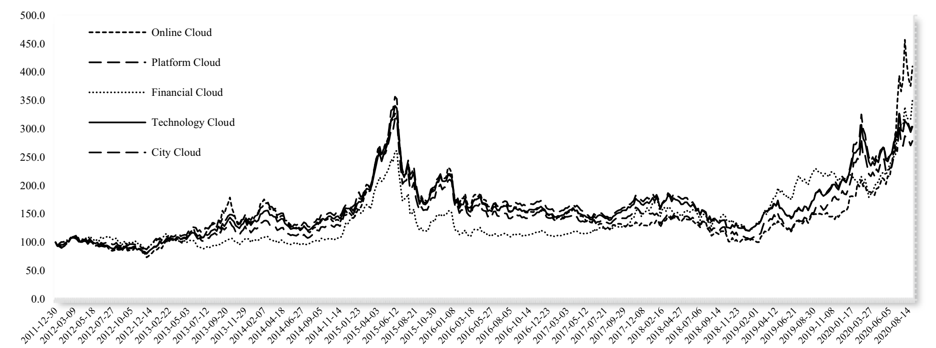


**Fig. 3** Performance of Primary Index Market. *Note* From January 1, 2012, to August 31, 2020, with weekly data

focus only on a single field/business. Therefore, we expect the correlations among these indices to be high; Table 4 presents what we expect. In particular, their high correlation is consistent with the idea that these five primary indicators can be used to explain similar or related concepts, such as cloud economy, which is a concept of aggregating five different key but related activities of the cloud economy.

### Analysis of the market performance of the first-tier indices

With the data of January 1, 2012 set as the baseline (100), Fig. 3, which plots the CCEI five first-tier indices, depicts the market performance of CCEI sub-index stocks.

## Market performance of CCEI

As all CCEI constituent stocks are selected from China's stock market, it is important to determine or calibrate their value or contribution to China's stock market. We use the weekly closing prices of the Shanghai Composite Index (SSE), Growth Enterprise Index (GEM), and CCEI from January 1, 2012 to August 31, 2020 and compare the above indices over time with the base date of January 1, 2012 (i.e., the initial value is set at 100). The reason for selecting SSE and GEM is that the former represents the overall behavior of China's stock market, whereas the latter is universally acknowledged as the epitome of the most influential and fast-growing listed technology companies.

Figure 4 depicts that CCEI experienced a significant structural change on January 11, 2019. Before this date, both CCEI and GEM closely moved with SSE. After that, CCEI and GEM moved away from SSE.

We also conduct several tests to determine if these indices are different from each other. First, we test whether the mean, median, and variance of CCEI, GEM, and SSE are really the same. Table 5 indicates that there is a significant difference in the mean, median, and variance of CCEI, SSE, and GEM because the $p$-values are less than 0.05, so we reject the null hypothesis that they are the same.

A plausible explanation for this sudden change is that the Chinese government's determination to develop the cloud economy continues to develop. According to the National Industrial Information Security Development Research Center (CERT 2019), as at the end of 2018, more than 34% of the provinces had issued policies that support digital and/or cloud economy, and approximately 25% had planned to formulate or issue relevant laws or policies. Thus, in terms of its top-level framework

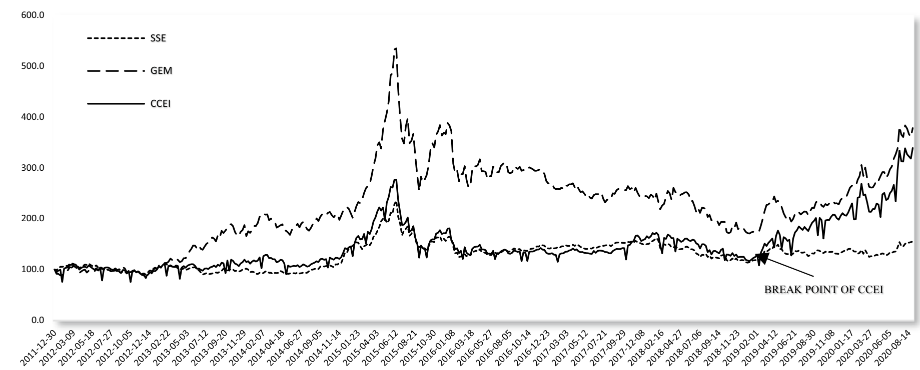


**Fig. 4** Chart of SSE, GEM and CCEI. *Note* From January 1, 2012, to August 31, 2020, with weekly data

**Table 5** Descriptive statistics of three indices

| | Mean | Median | SD | Kurt | Skew | Min | Max | Obs |
|---|---|---|---|---|---|---|---|---|
| CCEI | 156.6853 | 144.0976 | 49.4895 | 2.8471 | 1.5858 | 90.7576 | 358.3215 | 452 |
| SSE | 130.4579 | 133.9589 | 25.6035 | 0.8937 | 0.5728 | 91.4861 | 238.8075 | 452 |
| GEM | 246.8081 | 249.8904 | 87.7143 | 0.5762 | 0.3795 | 90.6952 | 582.9007 | 452 |

| X | Methods | *df* | F- test | *p* value |
|---|---|---|---|---|
| Mean | Anova F-test | (2, 1353) | 467.7024 | 0.00 |
| | Welch F-test* | (2, 756.637) | 387.7127 | 0.00 |
| Median | Med. Chi-square | 2 | 358.8496 | 0.00 |
| | Adj. Med. Chi-square | 2 | 356.1128 | 0.00 |
| | Kruskal–Wallis | 2 | 469.4183 | 0.00 |
| | Kruskal–Wallis (tie-adj.) | 2 | 469.4183 | 0.00 |
| | van der Waerden | 2 | 448.5861 | 0.00 |
| Variance | Bartlett | 2 | 598.5706 | 0.00 |
| | Levene | (2, 1353) | 183.5844 | 0.00 |
| | Brown-Forsythe | (2, 1353) | 174.6463 | 0.00 |

From January 1, 2012 to August 31, 2020, with weekly data

**Table 6** Spearman rank correlation between explanatory variables

| | CCEI | SSE | GEM |
|---|---|---|---|
| CCEI | 1.000 | 0.771 | 0.788 |
| SSE | 0.771 | 1.000 | 0.805 |
| GEM | 0.788 | 0.805 | 1.000 |

design and implementation path, the cloud economy has been gradually developed—so has its external environment. As a barometer of China's economy, the A-shares market is expected to follow a similar trend. Figure 4 depicts that after the break date, the overall performance of the cloud economy, as captured by the CCEI, is better than that of the overall A-shares market, and the gap between them gradually widens with time.

**Table 7** Dickey–Fuller test for unit root

| | **Test statistic** | | | | |
|---|---|---|---|---|---|
| | Level | Percent (%) | 1% Critical value | 5% Critical value | 10% Critical value |
| SSE: | | | | | |
| Drift | − 1.884 | − 19.630 | − 2.335 | − 1.648 | − 1.283 |
| Trend | − 2.133 | − 19.607 | − 3.982 | − 3.422 | − 3.130 |
| No-constant | 0.236 | − 19.612 | − 2.580 | − 1.950 | − 1.620 |
| CCEI: | | | | | |
| Drift | 1.056 | − 19.654 | − 2.335 | − 1.648 | − 1.283 |
| Trend | − 0.130 | − 19.688 | − 3.982 | − 3.422 | − 3.130 |
| No-constant | 1.969 | − 19.512 | − 2.580 | − 1.950 | − 1.620 |
| GEM: | | | | | |
| Drift | − 1.436 | − 19.543 | − 2.335 | − 1.648 | − 1.283 |
| Trend | − 1.737 | − 19.533 | − 3.982 | − 3.422 | − 3.130 |
| No-constant | 0.600 | − 19.393 | − 2.580 | − 1.950 | − 1.620 |

**Table 8** Bai and Perron critical values for CCEI

| **Panel A: Test for an unknown break** | **Test statistic** | **1% Critical value** | **5% Critical value** | **10% Critical value** | **Estimated break point** |
|---|---|---|---|---|---|
| H0: no break(s) vs. H1: 1 break(s) | 7.85 | 12.29 | 8.58 | 7.04 | 366 |
| Panel B: Test for a known break | W(tau) | *p*-value (F) | *p*-value (chi) | | Assumed break point |
| H0: no break(s) vs. H1: 1 break(s) | 24.75 | 0.00 | 0.00 | | 366 |

Motivated by the significant differences among the indices, we further check if they are highly correlated with each other. The results in Table 6 reveal that the correlation among CCEI, SSE, and GEM ranges from 0.771 to 0.805, suggesting that GEM and CCEI can be used to explain SSE. Therefore, we specify a regression model with CCEI and GEM as the explanatory variables of SSE.

## Regression analysis

### *Stationarity test*

To avoid the spurious regression problem, we first check if these variables are stationary. Table 7 presents the results of the unit root test. The results of the unit root test suggest that when measured in level, these variables mostly have a unit root problem; the exceptional case is that we can reject the null hypothesis (i.e., the unit root case) for CCEI at the 5% level when the alternative hypothesis is specified as a no-drift process. Even in this case, the null hypothesis can be rejected at the 10% level. However, these variables all are stationary when they are measured in percentage.

**Table 9** Performance of listed companies

| Industry | Project | | | |
|---|---|---|---|---|
| | Annual volatility | | Linkage with a-share market (beta) | |
| | Period 1 | Period 2 | Period 1 | Period 2 |
| CCEI | 47.9% | 44.7% | 0.912 | 1.181 |
| First-level indicators | | | | |
| PCI | 48.5% | 47.8% | 0.914 | 1.292 |
| OCI | 52.5% | 47.7% | 0.842 | 1.169 |
| TCL | 51.6% | 46.4% | 0.912 | 1.189 |
| CCI | 51.3% | 45.0% | 0.929 | 1.131 |
| FCI | 47.2% | 42.1% | 1.012 | 1.200 |

### *Structural break test*

As Fig. 4 seems to depict that there was a structural break with CCEI on January 11, 2019. We formally check this out using Bai and Perron's structural break tests (Bai and Perron 1998). Two versions of this test are available. The first version does not require us to pre-specify the break date, whereas the second version requires us to do so. The results of these two tests are presented in Panels A and B of Table 8. The first test reveals that there is one break date, and it is found at observation 366, which is January 11, 2019. The second test confirms that this break date is also statistically significant at the 1% level.

To further shed light on this issue, we check whether CCEI and its sub-indices experienced similar changes in their annual volatility and beta before and after the break. Table 9 reveals that the annual volatility of CCEI and its sub-indices all experienced a decrease in volatility after the structural break. City cloud experienced the largest decrease, followed by technology cloud and financial cloud, and the decline in the volatility of online cloud was close to that of CCEI. Among the five first-tier indices, only platform cloud experienced minimal changes.[1]

Turning to beta, we find an opposite pattern. In particular, the beta of CCEI and its sub-indices experienced increases after the break. For example, the beta of CCEI was 0.912 (1.181) before (after) the break. Prior to January 11, 2019, the relationship between the financial cloud index and the A-shares market was the strongest, whereas that of other sub-indices was slightly weaker. However, the relationship between these indices and the A-shares market strengthened sharply after the break. For example, the beta of platform cloud increased by 0.378. The performance of online cloud and technology cloud was also better than that of CCEI; their beta increased by 0.327 and 0.277, respectively, whereas the beta of CCEI experienced a rise of only 0.269. In summary, the evidence suggests that there was a structural break in the relationship between the cloud economy and the stock market in China. In particular, the cloud economy became less

[1] Some possible explanations include:
(1) The quantity and volume of technology companies is large, and the impact of these events is not enough to cause drastic changes to the indices. And.
(2) The information asymmetry in large technology companies is relatively low, and investor sentiment may have been fully digested by the market.

**Table 10** Least squares regression of SSE

| Model | (1) A | (2) B | (3) C | (4) D | (5) E | (6) F | (7) G |
|---|---|---|---|---|---|---|---|
| **Variables** | **SSE** | **SSE** | **SSE** | **SSE** | **SSE** | **SSE** | **SSE** |
| $\beta_1(CCEI)$ | 0.658*** | 0.634*** | 0.665*** | 0.646*** | 0.706*** | 0.706*** | 0.784*** |
| | (0.026) | (0.046) | (0.026) | (0.047) | (0.029) | (0.049) | (0.050) |
| $\beta_2(GEM)$ | | 0.025 | | 0.020 | | −0.001 | −0.078* |
| | | (0.040) | | (0.041) | | (0.041) | (0.042) |
| $\beta_3(DUM)$ | | | −0.005** | −0.005** | −0.002 | 0.003 | −0.003* |
| | | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_4(CCEI * DUM)$ | | | | | −0.183*** | −0.183*** | −0.598*** |
| | | | | | (0.050) | (0.051) | (0.101) |
| $\beta_5(GEM * DUM)$ | | | | | | | 0.524*** |
| | | | | | | | (0.108) |
| $\beta_6$(Constant) | −0.001 | −0.001 | 0.000 | −0.000 | −0.000 | −0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 451 | 451 | 451 | 451 | 451 | 451 | 451 |
| Adjusted $R^2$ | 0.679 | 0.679 | 0.683 | 0.683 | 0.692 | 0.692 | 0.713 |

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

risky (in terms of annual volatility) and more sensitive to stock market price movements. This is consistent with the view that investors perceived the cloud economy differently before and after the break (Table 10).

### *Regression results*

As Fig. 4 and the structural break test both reveal some structural changes in CCEI, we specify a set of regression models that consider this feature. The following regression models are specified:

(A) $SSE = \beta_{1A} * CCEI + \beta_{6A} + \varepsilon_A$

(B) $SSE = \beta_{1B} * CCEI + \beta_{2B} * GEM + \beta_{6B} + \varepsilon_B$

(C) $SSE = \beta_{1C} * CCEI + \beta_{3C} * DUM + \beta_{6C} + \varepsilon_C$

(D) $SSE = \beta_{1D} * CCEI + \beta_{2D} * GEM + \beta_{3D} * DUM + \beta_{6D} + \varepsilon_D$

(E) $SSE = \beta_{1E} * CCEI + \beta_{2E} * DUM + \beta_{5E} * (CCEI * DUM) + \beta_{6E} + \varepsilon_E$

(F) $SSE = \beta_{1F} * CCEI + \beta_{2F} * GEM + \beta_{3F} * DUM + \beta_{4F} * (CCEI * DUM) + \beta_{6F} + \varepsilon_F$

(G) $$SSE = \beta_{1G} * CCEI + \beta_{2G} * GEM + \beta_{3G} * DUM + \beta_{4G} * (CCEI * DUM) + \beta_{5G} * (GEM * DUM) + \beta_{6G} + \varepsilon_G$$

where SSE is the Shanghai Stock index; CCEI is CCEI, GEM refers to the GEM Index, and ε is the residual term. DUM is a dummy variable that takes the value of one if the observation occurs on or after January 11, 2019 and zero if otherwise. To capture the

**Table 11** Total variance explained

| Factor | Initial Eigenvalues | | | Extraction sums of squared loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative% | Total | % of Variance | Cumulative% |
| 1 | 4.555 | 91.106 | 91.106 | 4.555 | 91.106 | 91.106 |
| 2 | 0.296 | 5.913 | 97.020 | | | |
| 3 | 0.126 | 2.525 | 99.545 | | | |
| 4 | 0.021 | 0.422 | 99.967 | | | |
| 5 | 0.002 | 0.033 | 100 | | | |

Method: principal component analysis

possible interaction effect between DUM and GEM or CCEI, we construct two interactive variables with GEM and CCEI (i.e., GEM*DUM and CCEI*DUM). SSE, GEM, and CCEI are all measured in percentages. Moreover, GEM serves as a control variable because, similar to the U.S. GEM, this market is the cradle of incubated and growth enterprises and thus is expected to reflect the potential development of China's real economy.

Models (A) to (D) refer to some standard settings where the conditional and unconditional impacts of CCEI are considered. Models (E) and (F) are specified to allow for the possibility that the break may have an interaction effect on CCEI and GEM. Model (G) is the most general model that considers the impact of CCEI, GEM, and their interaction with DUM on SSE.

As expected, Model (G) performs better than Models (A) to (F) because its adjusted $R$-squared is the largest, which is 71.3%, implying that 71.3% of the variations in SSE can be explained by the variations in the GEM, CCEI, DUM, GEM*DUM, and CCEI*DUM. The dummy variable DUM greatly improves the performance of the models. For example, in Model (G), before January 11, 2019, CCEI played a leading role in explaining the variations of SSE, that is, every 1% change in CCEI is associated with a 0.784% change in SSE in the same direction. However, after January 11, 2019, the relationship between CCEI and SSE was weakened somewhat and its net relationship was 0.186% (0.784–0.598). Before the break, the relationship between GEM and SSE was always greater than or equal to 0.467, suggesting that GEM also plays an important role in explaining the variations in SSE before the break. However, its direct relationship became negative, whereas its indirect relationship through the break was much larger after the break. The overall relationship between GEM and SSE is that every 1% change in GEM is associated with a 0.446% ($-0.078+0.524$) change in the same direction of SSE, which is larger than that of CCEI, which is 0.186%. Therefore, the (unconditional) relationship between CCEI and China's economy had been strengthening throughout the sampling period. However, the variations of CCEI were no longer associated with that of SSE and stood on a new stage after the break. Because the performance of SSE (and thus the economy) was poor after the break, this finding is consistent with the view that the cloud economy has become a new source of economic growth in China as more supporting policies for the cloud economy development has been put in place not only at the national level but also at the provincial level.

**Table 12** Scoring coefficients

| Variable | Factor 1 |
|---|---|
| OCI | 0.06206 |
| PCI | 0.16095 |
| FCI | 0.09204 |
| TCI | 0.56637 |
| CCI | 0.14815 |

## Robustness check of the alternative measure of CCEI

As the five first-tier indices are highly correlated with each other, one may argue that there may be some common factors that are shared by these five indices, and they can be used as an alternative proxy for CCEI. We employ factor analysis to extract the first common factor and re-estimate the models, using this factor as an alternative proxy for CCEI. The result of the factor analysis is presented in Table 11, and the scoring coefficients of the first factor (called FACTOR 1) are presented in Table 12.

Several pre-tests are conducted to make sure that factor analysis is used properly. They are the Kaiser–Meyer–Olkin (KMO) test, Bartlett test, common factor variance test, and total variance test. The KMO test is used to compare the correlation coefficients and partial correlation coefficients between the variables, and the result of the KMO test on the five first-tier indices is 0.796, which meets the prerequisites for factor analysis. The Bartlett test is used to determine whether each variable is mutually independent, and the $p$-value of the Bartlett test is 0.00, which is less than 0.05, indicating that there is a correlation among the variables, and the factor analysis is valid. The common factor variance test is used to measure the degree of the explanatory power of the common factor of each variable, and the test indicates that the extract values of five variables are all higher than 0.7, suggesting that the common factor can explain these five variables satisfactorily. Finally, the total variance test is used to compare the contribution rates of factors to the interpretation of the variables. As presented in Table 11, the degree of the explanatory power of the first factor is up to 91.106%, indicating that the variations of the five sub-indices can be explained by a single common factor called FACTOR1. Table 11 reveals that TCI is the most important component to explain FACTOR1, as its scoring coefficient is 0.56637. PCI comes second and is followed by CCI.

Table 13 presents the regression results with FACTOR1 being used as a new independent variable to replace the CCEI in Models (A) to (G). The relevant equations are as follows:

$$\text{(A - 2)}\quad SSE = \beta_{1\mathrm{A}} * FACTOR1 + \beta_{6\mathrm{A}} + \varepsilon_A$$

$$\text{(B - 2)}\quad SSE = \beta_{1\mathrm{B}} * FACTOR1 + \beta_{2\mathrm{B}} * GEM + \beta_{6\mathrm{B}} + \varepsilon_B$$

$$\text{(C - 2)}\quad SSE = \beta_{1\mathrm{C}} * FACTOR1 + \beta_{3\mathrm{C}} * DUM + \beta_{6\mathrm{C}} + \varepsilon_C$$

$$\text{(D - 2)}\quad SSE = \beta_{1\mathrm{D}} * FACTOR1 + \beta_{2D} * GEM + \beta_{3\mathrm{D}} * DUM + \beta_{6\mathrm{D}} + \varepsilon_D$$

**Table 13** Regression result of alternative measure of CCEI

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Model** | **A-2** | **B-2** | **C-2** | **D-2** | **E-2** | **F-2** | **G-2** |
| **Variables** | **SSE** | **SSE** | **SSE** | **SSE** | **SSE** | **SSE** | **SSE** |
| $\beta_1$ (*FACTOR*1) | 0.022*** | 0.019*** | 0.022*** | 0.019*** | 0.024*** | 0.022*** | 0.028*** |
| | (0.001) | (0.003) | (0.001) | (0.003) | (0.001) | (0.003) | (0.003) |
| $\beta_2$ (*GEM*) | | 0.090 | | 0.086 | | 0.047 | − 0.112 |
| | | (0.066) | | (0.067) | | (0.068) | (0.068) |
| $\beta_3$ (*DUM*) | | | − 0.003 | − 0.003 | − 0.002 | − 0.002 | − 0.004** |
| | | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_4$ (*FACTOR*1 ∗ *DUM*) | | | | | − 0.006*** | − 0.006** | − 0.027*** |
| | | | | | (0.002) | (0.002) | (0.005) |
| $\beta_5$ (*GEM* ∗ *DUM*) | | | | | | | 0.691*** |
| | | | | | | | (0.137) |
| $\beta_6$ (Constant) | 0.001 | 0.001 | 0.002 | 0.001 | 0.002 | 0.001 | 0.002** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 451 | 451 | 451 | 451 | 451 | 451 | 451 |
| Adjusted $R^2$ | 0.574 | 0.577 | 0.575 | 0.578 | 0.584 | 0.585 | 0.615 |

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

$$\text{(E - 2)}\quad SSE = \beta_{1\mathrm{E}}*FACTOR1 + \beta_{2\mathrm{E}} * DUM + \beta_{5\mathrm{E}}*(FACTOR1*DUM) + \beta_{6\mathrm{E}} + \varepsilon_E$$

$$\text{(F - 2)}\quad SSE = \beta_{1\mathrm{F}}*FACTOR1+\beta_{2\mathrm{F}}*GEM+\beta_{3\mathrm{F}}*DUM+\beta_{4\mathrm{F}}*(FACTOR1*DUM)+\beta_{6\mathrm{F}}+\varepsilon_F$$

$$\begin{aligned}\text{(G - 2)}\quad SSE &= \beta_{1\mathrm{G}}{}^{*}FACTOR1 + \beta_{2\mathrm{G}} * GEM + \beta_{3\mathrm{G}}{}^{*}DUM \\ &\quad + \beta_{4\mathrm{G}}{}^{*}(FACTOR1^{*}DUM) + \beta_{5\mathrm{G}}{}^{*}(GEM^{*}DUM) + \beta_{6\mathrm{G}} + \varepsilon_G\end{aligned}$$

Similar to Tables 10, 13 reveals that Model G-2 provides the best data fit in terms of adjusted R-squared, and the *p*-values of its explanatory variables are mostly statistically significant. In Model G-2, before January 11, 2019, every 1% change in FACTOR1 is associated with a 0.028% change in SSE in the same direction. The relationship between FACTOR1 and SSE became much weaker (0.001 = 0.028–0.027) after the break. However, after the break, GEM became the main driver of SSE, where every 1% change in GEM is associated with a 0.691% change in SSE. Therefore, the regression results with FACTOR1 as an alternative measure of CCEI are similar to those with CCEI, suggesting that after the break, the performance of the cloud economy has been deviating from that of the real economy.

## Conclusion

Oracle predicted that by 2025, more enterprises will adopt the next generation of cloud business models to achieve unprecedented levels of automation. It is critical to track the trajectory of cloud economy growth, as it would soon become a barometer of national economic growth and international forward-looking competitiveness. To measure the status of cloud economy development and its relationship with the economy, we first define the basic concept of cloud economy and then construct a CCEI that is consistent with the definition using stock market data. The statistical properties of CCEI and its relationship with the overall stock market (as a proxy for the economy) are examined. The main finding is that the relationship between CCEI and the stock market has been getting stronger over time, but the availability of cloud-related policies has weakened this relationship, especially after January 11, 2019.

## Appendix: Important events related to cloud in 2020

January 20—UCloud landed on STAR Market and became the first cloud computing stock in China. Daily Economic Weekly. https://baijiahao.baidu.com/s?id=1657582146783128845&wfr=spider&for=pc. Accessed 20 Jan 2022.

March 5—JD integrated the three brands to establish the "JD Cloud & AI" brand. China Byte. https://ai.chinabyte.com/402/1531031402.shtml. Accessed 20 Jan 2022.

May 8—Kingsoft Cloud landed on NASDAQ. Economic Daily. https://baijiahao.baidu.com/s?id=1666174547789335397&wfr=spider&for=pc. Accessed 20 Jan 2022.

May 18—Baidu CTO Wang Haifeng announces the new strategy of Baidu intelligent cloud. Drive China. https://baijiahao.baidu.com/s?id=1667013020673881841&wfr=spider&for=pc. Accessed 20 Jan 2022.

August 17—Huawei Cloud is listed in the "Entity List" by the United States. Fast Technology. https://baijiahao.baidu.com/s?id=1675284896416310672&wfr=spider&for=pc. Accessed 20 Jan 2022.

September 27—Alibaba Cloud released the "Cloud Nailing Integration" strategy. Sina Technology. https://finance.sina.com.cn/tech/2020-09-27/doc-iivhvpwy9195501.shtml. Accessed 20 Jan 2022.

October 8—IBM plans to spin off GTS's managed infrastructure services division and establish a new company. Sohu. https://www.sohu.com/a/423482192_700450. Accessed 20 Jan 2022.

November 17—PingCAP received US $270 million in financing, creating a new global database record. Financial Circles. https://baijiahao.baidu.com/s?id=1683596285223139807&wfr=spider&for=pc. Accessed 20 Jan 2022.

November 25—AWS suffered downtime, leading to the collapse of some websites and service systems. Leiphone.https://baijiahao.baidu.com/s?id=1684396939171666360&wfr=spider&for=pc. Accessed 20 Jan 2022.

December 15—Google server suddenly suffered a large area of global downtime. Leiphone. https://baijiahao.baidu.com/s?id=1686075236573213961&wfr=spider&for=pc. Accessed 20 Jan 2022.

December 21—IBM announced the acquisition of cloud consulting service provider Nordcloud. Sina Finance. https://baijiahao.baidu.com/s?id=1686709321214224310&wfr=spider&for=pc. Accessed 20 Jan 2022.

**Abbreviations**

CCI: City Cloud Index; CCEI: China Cloud Economy Index; CHIT: Global X MSCI China Information Technology ETF; FCI: Financial Cloud Index; GEM: Growth Enterprise Index; ICT: Information and Communications Technologies; OCI: Online Cloud Index; PCI: Platform Cloud Index; PKU-DFIIC: Peking University Digital Financial Inclusion Index of China; SSE: Shanghai Composite Index; TCI: Technology Cloud Index.

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**Authors' contributions**
Conceptualization: LL; methodology: LL and AC; Software: LL and AC; Validation: LL and AC; Formal analysis: LL and AC; Investigation: LL; Resources: LL; Data Curation: LL; Writing—original draft: LL; Writing—review and editing: LL and AC; Visualization: LL and AC; Supervision: AC; Project administration: AC; Funding acquisition: AC. All authors read and approved the final manuscript.

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**Data availability**
The data that support the findings of this study are available from [Hithink Royal Flush Information Network Co., Ltd.] but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the first author upon reasonable request and with permission of [Hithink Royal Flush Information Network Co., Ltd.].

## Declarations

**Competing interests**
The authors declare that they have no competing interests.

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