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Digital Social Assets: Identification, Valuation, and Pricing -Evidence from KOL Transaction Market in China

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Abstract: The social behavior of individuals or organizations will form social capital. Social behavior based on the internet forms digital social capital. This paper focuses on the identification, measurement, and pricing of digital social capital, which will contribute to the current research of social capital. We constructed a pricing model of digital social capital and conducted an empirical analysis based on the KOL exchange data. The main factors that affect social capital value are social behavior efficiency and recent social behavior efficiency. However, the link width (especially the number of followers) of social capital has no significant effect on pricing.

1. Introduction

In the era of big data, digital assets have become a valuable asset, among which digital social assets are a new field. There are not enough research results on identifying, managing, trading, and financing social assets. This paper discusses the identification, valuation method, and transaction model of digital social assets, which will provide a useful supplement for the research of social behavior data capitalization

Social activities include non-internet based social activities and internet-based social activities. Internet-based social activities include social activities based on Internet platforms, such as Weibo and Twitter. Social activities based on the Internet platform divide into two basic types: one is entirely open social activities, and anyone can search other people's social content (such as Weibo articles); the other is a private social mode, such as WeChat. If you need to socialize with specific people, you need to get permission from the other party to form a friendly relationship before seeing the other party's social activities behavior. In WeChat, if we need to view the content shared by a person's circle of friends, we need to get the person's certification permission and add us to his friends' list before we can see it.

Social data formed by social activities based on Internet platform (creation of social content, social discussion, the formation of the relationship of concern and being concerned, the praise of social content, forwarding of social content, etc.). The social data and the social account controlled by social actors. This social resource brings benefits to social actors. We define this kind of social resource to be digital social assets. In the existing literature, such social resources defined as social capital, too. In this paper, we do not distinguish social capital and social asset. By default, these two concepts are the same.

In this paper, we mainly discuss the social assets based on the Internet, digital social assets. Digital social assets are traceable (such as links to friends, follow and followed relationships), traceable (such as when social behaviors occurred), and discoverable (browsable). It is precisely because of these characteristics of digital social assets that we believe that it is possible for digital social assets to be economical and financial and to be able to carry out quantitative valuation and pricing.

The difficulties in the economic and financial development of digital social assets lie in: first, to evaluate digital social assets. To evaluate digital social assets accurately, we must identify the core features that affect the value of digital social assets, quantify these features, and find the relationship between these features and value. 2. How to price. There is a correlation between asset value and price, but asset price also relates to market supply and demand. Therefore, in terms of asset pricing, we need to take other factors that affect pricing into consideration. Only in this way can we develop a feasible pricing framework to analyze and predict the transaction price of digital social assets.

There are several traditional asset valuation methods, such as the historical cost method, net value method, NPV, and market value method. In our opinion, the conventional historical cost method, net value method, and discount method are not suitable for the valuation of digital social assets. Although the acquisition of social assets needs to pay costs, including establishing and maintaining relationships (Adler & Kwon, 2019), it is difficult to measure the costs of social behaviors, such as the cost of creating a video by one person and then sharing the video to friends in the social circle. In addition, the net worth method and the NPV method are not applicable to the valuation of digital social assets because the data such as the time of realization, the costs that may need to pay in the future are also unavailable. Therefore, this paper proposes a better way to value digital social assets by market value method because in the field of social assets, there is a model based on KOL transaction, and KOL itself is the social account operator.

The value of digital social assets lies in three aspects. Firstly, the value to social account operator itself, such as the sense of trust and happiness brought to social account operator itself. Secondly, the value to the Internet platform, such as the greater user stickiness brought to the Internet platform providing social activities. Finally, the value to other partners, such as digital social assets to business partners. Some articles focus on the value of social capital to individual social account operators, such as powdthavee1 (2007); others focus on the value of social assets to Internet platforms, such as Kim & Chung (2018). This paper analyzes the value of digital social assets to other parties. As far as we know, this is the first article to analyze social assets from the perspective of bringing value to third parties. We believe that our research will bring new value to the study of social assets.

This paper argues that the value that digital social assets bring to the third party (such as commercial companies) relates to the third party's price to purchase such capital or resources. Therefore, this paper uses the trading data of KOL (key opinion leader)[1], and takes KOL trading price[2] as the representative of the value of digital social assets, analyzes the influencing factors that

[1] KOL refers to the social subject with a wider social relationship. KOL generally has a wide range of social relations, and is active in social networks. They express their views and opinions, and ultimately affect other people in the social circle.

[2] KOL transaction refers to that the commercial entity (generally the company) signs a contract with KOL, and the commercial entity pays KOL, while KOL temporarily transfers the right to use its social account to the commercial company (once or more), to help the commercial entity achieve the purpose of broadcasting the designated commercial information to KOL's social circle. The materials may prepared by companies, and KOL only needs to forward these information to its own social circle, that is, the forwarding mode; or, KOL can write the broadcast content according to the requirements of the commercial subject, and then broadcast to its own social circle. It shows that the essence of KOL transaction is to realize the economic and financial development of social assets.

affect the trading price of digital social assets, that is, to find the driving factors that determine the value of digital social assets. Our empirical study finds that there is a positive correlation between historical social efficiency and price, while there is a negative correlation between recent social efficiency and price. At the same time, we found that there was no significant correlation between social breadth (such as the number of fans) and pricing.

Our research has provided academic contributions in the following aspects: firstly, this paper proposes the research direction of digital social assets and promotes the study of social capital to the field of digital social assets. Secondly, this paper constructs a research paradigm of digital social capital and proposes a method to quantify social characteristics based on the social breadth, historical social efficiency, and recent social efficiency. Furthermore, this paper connects social features with the valuation and pricing of digital social assets. Thirdly, based on KOL trading data, we make an empirical analysis on the factors affecting the value and price of digital social capital, providing new evidence for the value source of social assets.

The following chapters arranged as follows: in Chapter 2, we summarize the relevant literature of social assets; in Chapter 3, we define digital social capital, and propose hypotheses and empirical models for the research; in Chapter 4, we will conduct an empirical analysis on the factors affecting digital social assets. The last part is the conclusion.

2. Social capital definition and measurement

2.1 What is social capital

Fulkerson & Thompson (2008) pointed out that most articles on social capital did not clearly define social capital. However, in most reports, the words related to social capital mainly include networks, resources, relationships, trust, reciprocity, individuals, and norms.

Social capital also relates to ease of cooperation and network (palm, 2000). Social capital involves group cooperation and intragroup network (palm, 2000). According to Harpham (2002), the generation and maintenance of social capital is mainly in similar groups or groups with the same social environments, such as a community or youth group.

In the research of social capital, many articles study social capital and source together. For example, Chiu, Hsu, & Wang (2006) think that productive resources and social capital are closely

Related (Chiu, Hsu, & Wang, 2006). As early as the 1980s, Bourdieu mentioned that social capital is the sum of real or potential resources in the relationship network (Bourdieu 1985). Coleman (1990) indicated that relationships, trust, and the power of voluntary distribution belong to the resources of individuals.

Baker (1990) pointed out that social capital driven by social structure and pursued interests. Schiff (1992) proposed that social capital is a set of elements related to production input and utility function. Burt (1992) said more directly. Burt defines social capital as good friends, colleagues, and other broader good relationships through which individuals can better access to financial and human capital. The social capital can group into two elements: first, the social relationship itself allows individuals to ask for resources owned by their partners; second, the quantity and quality of these resources (Portes, 1998). Social capital significantly relates to the degree of resource exchange between units, which significantly affects product innovation (Lester, 2013).

2.2 The value of Social capital

Although there are different ideas about the definition and scope of social capital, Portes, A. (2000) believes that most of the research focuses on the benefits and values of social capital and social ties to individuals and families. The value of social capital exists in three aspects: the value on social account operator, which includes trust, respect, control over things, etc.; the value on the social platform, including economic value and non-economic value; and the value on business partners, which mainly relatesto commercial benefit.

The research on social capital value to social account operators mainly focuses on the personal psychological value of social assets, such as the sense of happiness and trust brought by social assets. The trust and voluntary behavior implied by social capital have an essential impact on individual happiness (Putnam, 2000; Helliwell, 2003). People with productive social relations tend to live happier lives (Burt, 1987). Social capital is similar to public goods close to the individual utility function. Positive externalities will lead to better results, and individuals will be more willing to invest in social capital (Becker, 1996). In one study, scholars focused on the impact of using Facebook on individuals. They found that the use of Facebook has significant benefits those users that experienced low self-esteem and life satisfaction (Ellison, steinfield, & Lampe, 2007). Online social behaviors will bring more far-reaching effects to individuals. For example, the study of online role-playing games found that through online cooperation, players become lifelong friends because they encourage and share things on the Internet while ignoring the gender differences and ages that may concern in real life (Cole & Griffiths, 2007).

After controlling other factors, interpersonal trust is an essential predictor of individual participation attitude and behavior, for example, whether individuals will participate in voting, political activities, and other activities (knack & Keefer, 1997). Palmam (2000) pointed out that trust building and cooperation are integral. Therefore, social capital is a kind of 'soft' social sciences. In the virtual network, social capital can affect knowledge sharing behavior because social capital has the characteristics of association, trust, affirmation, and so on (Chiu et al., 2006). The repeated interaction between the parties produces faith, and the expected return present value of future communication is higher than the return of betraying the current transaction (knack & Keefer, 1997).

When social account operators create social capital through their efforts, they will also provide value creation for platforms providing social interaction, increase content and increase users' stickiness to social media. Relational embeddedness has a positive impact on enterprise performance (batjargal, 2003). Social capital can connect different individuals, play an intermediary role, and promote the voluntary behavior of individuals (Chiu et al., 2006). Social capital is significant for cooperation (Putnam 1993). Social capital may improve the enhancement levels of awareness of control. De Carolis et al. (2009) pointed out that there is a correlation between social capital and new venture creation, which has an impact on risk prosperity. The social network must construct through the investment strategy of group-oriented Institutionalization (Portes, 1998)

The value of social capital to business partners lies in that by sharing their social relations, social capital owners can provide value to business partners, including increasing trust, contacting actual and potential users. Influencing ability and linking ability are two values of social capital. A person's behavior is associated with the social network influences (Chiu et al., 2006). According to de Carolis, litzky, & eddleston (2009), "bonding" social capital and "bringing" social capital are two kinds of identified assets of social capital. Using social capital, social subjects bring value to partners in bonding and bringing, especially in business communication and brand image building, and the amount of social capital is reflected.

2.3 Social capital Measurement and Economization

It is difficult to measure the value of digital social assets. Still, there are also many kinds of literature trying to measure the first value (economic value of social support to individual happiness and other psychological aspects) and the second value (monetary value of social assets to social platforms).

Nattavudh Powdthavee (2007) measured the value of social capital (interaction frequency with friends, relatives, neighbors, etc.) through shadow price and found that the value of social capital for individuals reached £ 85000 every year.

Kim & Chung (2018) studied the value model of social capital reward through token economy design. Steemit associates social capital with cryptocurrency. On the Steemit social platform, users will reward for their social activities (post, like, etc.). Steemit evaluates each user's contribution and rewards those who create social value by issuing the cryptocurrency. Assess everyone's social value fairly is very important for the development of Steemit. Steemit uses up to 75% of its annual cryptocurrency to reward users who participate in social interactions (creating content, liking content, commenting, etc.). For Steemit users, any social data they form will be recorded, and enter the evaluation system to participate in the calculation of encrypted data rewards; for users, social record and social connection is their social capital.

Based on blockchain technology, Steemit has designed three different forms of encrypted digital currency, steem, steem dollar, and steem power. Ordinary users can get the reward of cryptocurrency through social activities. Users can set the kind of reward they prefer most, the steem, or the steem power. Steem power holders have more power in recognizing who contributes more to the community so that steem power can be similar to a shareholder of steemit. Different currencies can convert. For example, the steem dollar can convert to steem at a constant value. Steemit stipulates that at any time, users can turn a steem dollar into a steem that equivalent to the market price of $1. Therefore, the steem dollar is similar to the convertible bond of the company of Steemit. Through this design, the stable currency value of the steem dollar maintains, which helps users to assess the value of Steemit's encrypted digital currency from a longer-term perspective (Kim & Chung, 2018).

At present, there is no specific article on measuring the value of social capital to third-party business partners. To the best of our knowledge, our article is the first one to quantify the value and pricing drivers of social assets in the cooperation between social assets and third parties. Therefore, our research will provide a great supplement to the current study.

3. Theoretical background, hypothesis development and models

3.1 Definition of digital social assets

In this paper, we define digital social assets as the sum of digital social resources formed through historical social events based on internet-based social platforms.

Assets usually refer to the resources formed by past transactions or events, controlled or mastered by the owner, and expected to bring economic benefits to the owner. Therefore, there are three basic attribute requirements in the meaning of assets: Firstly, assets forms by historical transactions or events. Secondly, assets controlled or mastered by the owner. Thirdly, assets expected to bring benefits.

Digital social behavior refers to how people transfer information and exchange ideas based on the Internet platform. On the internet platform, the social behavior of the social account operator will be recorded, and the social data formed at the same. The social source controlled by the social account operator, which can transform into economic effect through encrypted data or KOL transaction, so the essential attributes of assets are satisfied.

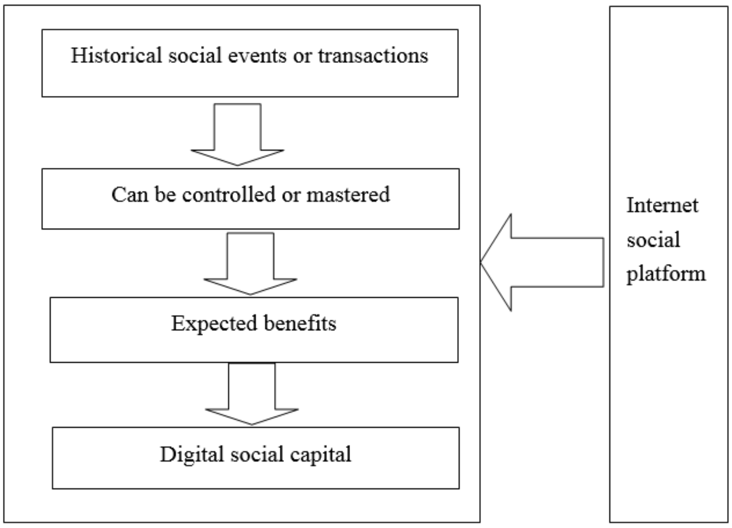

Figure 1: Social assets

In digital social communication, social account operators can choose whether to participate in the establishment and maintenance of social relations, or they can choose to quit a certain kind of social relations. Therefore, social account operators do not have the problem of insufficient social control. Under certain circumstances, the internet-based social platform has a particular impact on social account owners. For example, the algorithm settings of the platform give priority to some social accounts in social account search results, which increases the exposure opportunities of social accounts. However, from the perspective of the nature of social interaction, the intervention of social platforms has not changed the nature of social relation

3.2 Value discussion of digital social assets

The behaviors, outputs, and values involved in the social process based on Internet platform summarized as follows Table 1:

Table 1: The output and value of social assets

	behaviors	outputs	values
1	Content creation	Articles, pictures, audio, video, etc	Sharing: knowledge, experience, interesting things, etc
2	Share social content	Sharing data	Content broadcast to a wider audience
3	Participation in Reviews or Comments	Comment content	Social interaction, forming different opinions, etc
4	Like/up-vote social content	Like/up-vote data	Social interaction helps to select the most praised content, etc
5	Follow or be followed	Become a fan of others and pay attention to others, or others become their own followers	Forming social connections and networks

We show the above information in a hierarchical relationship, as shown in Fig.2

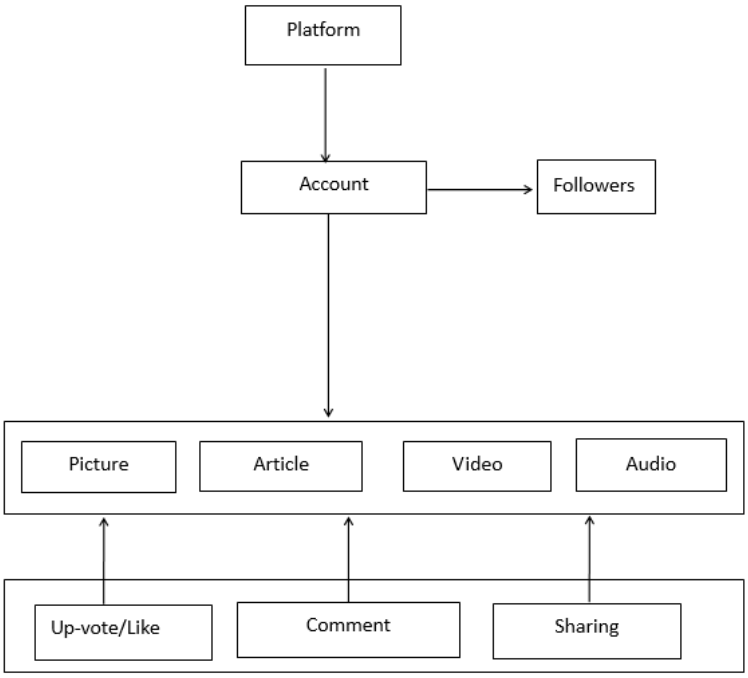

Figure 2: The structure of social platforms

As can be seen from the figure above, social accounts record social outputs, reflecting the ability and impact of social interaction. We further define digital social capital as follows: digital social assets are the sum of resources formed by social behavior on the internet-based platform and controlled by specific accounts, which expected to benefit social account operators in the future. Here, we make it clear that social account operators do not distinguish between individuals and institutions. Social account operators refer to registered owners of social accounts.

3.3 Hypothesis proposed

The social account operator can use or cancel the social account, and the transfer of the right to use the social account can bring benefits to the social account operator. In this paper, we mainly evaluate the digital social capital based on the price of the social account operators transferring the right to use the account. There are several forms of the temporary transfer of the right to use a social account: to create and display the content of partners or to forward the specified content.

The temporary transfer of the right to use social accounts is a kind of transaction. From the perspective of transaction essence, the account operator obtains the money based on the deal. The party that purchases social assets need to pay for the social account owners.

The core value of digital social assets embodies in two main aspects: link width and link efficiency. The range of links is mainly the reachability of fans. Therefore, link width is related to the number of fans, the number of social content (including articles, videos, audio, etc.), while the link efficiency is associated with the number of likes, comments, and forwarding of social content.

There are differences in identifying social account operators, for example, whether the subject is an ordinary user or a public figure. If the social account operator is a TV actor or singer, the trust and stickiness of fans may be higher. We introduce the variable of Public_figure to control this difference in identification. If the social account operator is a TV host, or other types of the host, the value of Public_figure defaults to 1. If the social account operator is an actor, the value of the

Public_figure defaults to 2. If the social account operator is a singer, the Public_figure defaults to 3; if the social account operator has multiple identifications, the Public_figure is 4 by default; if the public identity of the social account operator are other identifications, the Public_figure defaults to 0.

Table 2: Variables

Parts	Sub_parts	Details	Variable_name
Core value	The breadth of social activity (width)	Number of fans	Followers
		The number of social content released in history (including articles, videos, audio, etc.)	History_public
		The largest number of published content (including articles, videos, audio, etc.) in a single day	Highest_public_perday
		On average, how many days will a designated social account post a social content	Frequency
	Historical efficiency of social activities (his_eff)	The average number of views per social content	Ave_view
		The average number of likes per social content	Ave_vote
		The average number of comments per social content	Ave_comment
		The average number of forwarding per social content	Ave_forward
		Of all social content, the largest number of forwarding	Highest_forward
		Of all social content, the most praised	Highest_vote
		Of all social content, the most commented	Highest_comment
	Recent efficiency of social activities (current_eff)	Average views of the latest 30 social content	
		The average number of likes in the last 30 social content	Ave_vote_latest
		The average number of comments on the latest 30 social content	Ave_comment_latest
		The average number of social content forwarding in the last 30	Ave_forward_latest
		The highest number of social content forwarding in the last 30	Highest_forward_latest
		Top likes of the latest 30 social content	Highest_vote_latest
		The highest number of comments on the latest 30 social content	Highest_comment_latest
		The highest number of social content forwards in the last 30	Highest_forward_latest
		Total number of comments on the last 30 social content	Total_comment_latest
		Total likes of the last 30 social content	Total_vote_latest
		Total likes of the last 30 social content	Total_forward_latest
Controls (CV)	Other factors	The first transaction mode: Content Creation + content display; the second transaction mode: only forwarding content	Trade_type:produce Trade_type:forward
		Industry type	Industry_type
		Types of public figures	Public_figure

We introduce industry variables to control industry differences. Our identification of the industry mainly base on the description text or keyword information set by the social account operator.

In the transaction of social resources, there are generally two basic transaction modes. One is to use a social account to help the third party (usually commercial companies) to spread information. This method realizes by the social account operator forwarding the specified content in its social account. The second transaction mode is that the social account operator creates social content according to the contract requirements and publishes the content in its social account. In the second transaction mode, the social account operator deeply involves in content creation and content publicity. We define the first mode as trade_type: forward, and the second mode as trade_type: produce.

We summarize the variables that may affect the transaction price of social capital, as shown in Table 2:

Based on the above analysis, we propose the following assumptions: Based on the above analysis, we present the following assumptions:

H1: under the same conditions, the value/price of digital social assets positively relates to the breadth of social capital

H2: under the same other conditions, the value/price of digital social assets positively relates to the historical efficiency of social capital

H3: under the same other conditions, the value/price of digital social assets has a positive correlation with the near-term efficiency of social assets

3.4 Empirical models

The social capital-pricing model of digital social assets is as follows:

$$Price=\alpha+\beta1*width+\beta2*his\_eff+\beta3*current\_eff+\beta4*CV+\mu \quad (1)$$

Price refers to the transaction price of digital social assets, width refers to social breadth, his_eff refers to the historical social efficiency, current_eff refers to recent social efficiency, and CV refers to other factors.

4. Empirical analysis

4.1 Data source and sampling

In KOL trading, commercial companies or other individuals value KOL's social relations (linkability, influence, etc.), so the price of KOL trading reflects the value of social assets owned by KOL to some extent. In this paper, we use the price of KOL transaction as a proxy variable of social capital price to measure the value of digital social assets.

Our data comes from KOL trading data of kuaichuanbo (711.cn). The kuaichuanbo website is a KOL trading center, which provides KOL's social account information (number of fans, number of forwarding, number of likes, number of comments, etc.) and trading price information. Commercial companies can select online target cooperation KOL. After the subscriber completes the payment process, based on the subscription contract, KOL will publish the social content specified in the contract (or create social content and then publish it). Our sample includes transaction data of 9784 KOLs, all of which base on Weibo.com. For details, see table3:

Table 3: The data type of KOL exchange

Data	Details
Basic information of KOL	The number of fans, number of likes, evaluation data, sharing data, etc. These data divides into all historical data and the latest 30 days.
Other information of KOL	Geographic location, industry, public figure type
Transaction price	Transaction price

4.2 Descriptive statistics

We make basic statistics on variables, such as table 4.

As can be seen from the results of Table 4, the proportion of KOLs identified as hosts, singers, and actors in all KOLs is relatively low, only 0.9%. There is a significant gap in the number of fans of each KOL. The average minimum amount of fans of all KOLs is 1860, while the average number of fans of KOL is 2140000. The price of the KOL transaction is very different, the lowest price is 16, while the highest price is 1590000, and the average number is 12083.61.

Table 4: Summary of variables

Variable	Obs	Mean	Std.Dev.	Min	Max
Public_figure	9784	.009	.129	0	4
Frequency	9674	9.132	26.802	1	658
Followers	9784	2140000	2370000	1860	2.71e+07
Ave_forward	9784	582.928	1910.023	1	65300
Highest_forward	9784	3032.18	13048.49	1	532000
Ave_vote	9784	1705.481	36927.86	1	2560000
Highest_vote	9784	7192.553	60187.78	0	3760000
Ave_comment	9784	430.384	2044.161	1	91800
Highest_comment	9784	2049.993	10307.06	0	424000
Price	9784	12083.61	49630.26	16	1590000
Total_forward_latest	9635	8087.472	75410.52	1	4840000
Ave_forward_latest	9202	291	2575.576	1	161000
Highest_forward_latest	9635	1575.88	10451.8	1	574000
Total_comment_latest	9676	6973.347	49202.79	1	2570000
Ave_comment_latest	9071	252.332	1694.739	1	85662
Highest_comment_latest	9676	1095.71	6419.6	1	207000
Total_vote_latest	9706	28566.35	203000	1	6730000
Ave_vote_latest	9611	970.334	6807.764	1	224000
Highest_vote_latest	9706	7279.227	49876.93	1	2340000
History_public	9713	14091.95	24082.64	1	345000
Highest_public_perday	9717	15.442	16.117	1	105

According to KOL data, KOL publishes social content every nine days (average of 9.132). There is a vast difference in the number of times social content is forwarded. The minimum number of times is one, the maximum amount is 65300, and the average number of times is 582.928. Similarly, the average number of likes and comments on social content varies significantly among different users. See Ave_vote and Ave_comment.

From the highest social interaction data, the highest number of forwarding of a single social content is 532000, while the highest number of commented is 424000, and the highest number of being praised is 3760000. We can see that popular social content has a profound impact on dissemination. There are also considerable differences in social content performance in the last 30 days, such as the number of likes, forwards, and comments among different social content.

On average, all KOLs published social content 14091.95 times, and the total number of KOL accounts with the most content publishes 345000 pieces of social content. On average, a single KOL publishes 15.442 articles of social content every day. The average number of KOL accounts with the most communicative content publishes 105 pieces of social content every day. As you can see, some KOLs spend a lot of effort to maintain social contact.

As shown in table 5, KOLs mainly distributed in news and info, fashion, and other industries.

Table 5: Statistics of industries

Industry_type	Freq.	Percent	Cum.
Ad_and_Marketing	20	0.21	0.21
Beauty_makeup	591	6.17	6.38
Campus	142	1.48	7.86
Car	236	2.46	10.33
Constellation	64	0.67	10.99
Culture	12	0.13	11.12
Digital	173	1.81	12.93
E-commerce	6	0.06	12.99
Education	48	0.5	13.49
Emotion_sentiment	795	8.3	21.79
Entertainment	722	7.54	29.33
Fashion	829	8.66	37.98
Film_and_TV	501	5.23	43.21
Finance_and_Economics	167	1.74	44.96
Food	486	5.07	50.03
Fun_and_Joke	237	2.47	52.51
Game	318	3.32	55.83
Gymnastic	113	1.18	57.01
Handmade	2	0.02	57.03
Health	21	0.22	57.25
Home_furnishing	82	0.86	58.1
Internet	90	0.94	59.04
Life	145	1.51	60.56
Literature_and_art	110	1.15	61.7
Military	74	0.77	62.48
Mother_and_infant	409	4.27	66.75
Music	12	0.13	66.87
News_and_Info	934	9.75	76.62
Other	1,847	19.28	95.91
Outdoor	2	0.02	95.93
Pets	45	0.47	96.4
Sports	40	0.42	96.82
Technology	59	0.62	97.43
Travel	246	2.57	100
Total	9,578	100	

Table 6 shows the statistics of KOL's region. In addition to the KOL labeled nationwide, Beijing (1825), Guangdong (944), and Shanghai (698) have the largest number of KOLs. All three regions are the most developed in China. In addition, there are a large number of KOLs from outside mainland China. The number of overseas is 684, accounting for 7.14%

Table 6: Statistics of districts

District	Freq.	Percent	Cum.
Anhui	27	0.28	0.28
Beijing	1,825	19.05	19.34
Chongqing	87	0.91	20.24
Fujian	177	1.85	22.09
Gansu	6	0.06	22.15
Guangdong	944	9.86	32.01
Guangxi	24	0.25	32.26
Guizhou	6	0.06	32.32
Hainan	12	0.13	32.45
Hebei	35	0.37	32.81
Heilongjiang	21	0.22	33.03
Henan	84	0.88	33.91
Hongkong	54	0.56	34.47
Hubei	95	0.99	35.47
Hunan	92	0.96	36.43
Jiangsu	276	2.88	39.31
Jiangxi	26	0.27	39.58
Jilin	24	0.25	39.83
Liaoning	77	0.80	40.63
Macao	18	0.19	40.82
Nationwide	3,187	33.27	74.1
Neimenggu	6	0.06	74.16
Ningxia	2	0.02	74.18
Other	434	4.53	78.71
Overseas	684	7.14	85.85
Shandong	102	1.06	86.92
Shanghai	698	7.29	94.21
Shanxi	28	0.29	94.5
Shanxi_1	46	0.48	94.98
Sichuan	158	1.65	96.63
Taiwan	19	0.20	96.83
Tianjin	46	0.48	97.31
Yunnan	39	0.41	97.71
Zhejiang	219	2.29	100
Total	9,578	100.00	

Note: the Shanxi is the eastern *province, and Shanxi_1 is the western province.*

Table 7 shows the statistics of the *Public*_figure. It shows that the types of Public_ figure with clear identities are mainly hosts and actors.

Table 7: Statistics of public figures

Public_figure	Freq.	Percent	Cum.
0	9,732	99.47	99.47
1	26	0.27	99.73
2	22	0.22	99.96
3	2	0.02	99.98
4	2	0.02	100
Total	9,784	100	

4.3 Empirical result

4.3.1 Factor analysis

In the empirical part, we first refine the factors. Therefore, we perform factor analysis on the variables related to the core pricing part, and the results show in Table 8. From table 8, we can see that factor 1, factor 2, and factor 3 are factors with an eigenvalue greater than 1, and these three factors explain the total variance of 0.8792.

Table 8: Factor analysis for all core variables

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	6.26207	3.21719	0.5257	0.5257
Factor2	3.04488	1.87812	0.2556	0.7813
Factor3	1.16676	0.4419	0.0979	0.8792
Factor4	0.72486	0.17726	0.0608	0.94
Factor5	0.5476	0.26937	0.046	0.986
Factor6	0.27823	0.05601	0.0234	1.0094
Factor7	0.22222	0.06739	0.0187	1.028
Factor8	0.15483	0.05001	0.013	1.041
Factor9	0.10482	0.10442	0.0088	1.0498
Factor10	0.0004	0.00043	0	1.0498
Factor11	-0.00004	0.00011	0	1.0498
Factor12	-0.00015	0.02737	0	1.0498
Factor13	-0.02751	0.04199	-0.0023	1.0475
Factor14	-0.0695	0.04949	-0.0058	1.0417
Factor15	-0.11899	0.02659	-0.01	1.0317
Factor16	-0.14559	0.08642	-0.0122	1.0195
Factor17	-0.232	.	-0.0195	1

Table 9: KMO results

Variable	kmo
Followers	0.8142
Frequency	0.5299
Ave_forward	0.562
Highest_forward	**0.4464**
Ave_vote	0.5781
Highest_vote	0.5837
Ave_comment	0.8588
History_public	0.5305
Highest_public_perday	0.5275
Ave_vote_latest	0.6241
Ave_comment_latest	0.6412
Ave_forward_latest	0.678
Highest_comment_latest	0.8649
Highest_forward_latest	0.8812
Total_comment_latest	0.6413
Total_vote_latest	0.6235
Total_forward_latest	0.6809
Overall	0.669

From the results of Table 9, we can see that the kmo value of Highest_forward is 0.4464, less than 0.5, which is not suitable for factor analysis

After removing the highest "forward" variable, we conduct factor analysis on the remaining variables again, and the results show in table 10. It shows that the eigenvalue of factor1, Factor3, and factor1 are all greater than one, and the cumulative variance of the three factors is 0.9447, so we consider using only these three factors.

Table 10: Factor analysis result after removing low kmo variable

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	6.26199	3.73997	0.5945	0.5945
Factor2	2.52202	1.35528	0.2394	0.8339
Factor3	1.16673	0.61754	0.1108	0.9447
Factor4	0.54919	0.27083	0.0521	0.9968
Factor5	0.27836	0.08472	0.0264	1.0232
Factor6	0.19363	0.08679	0.0184	1.0416
Factor7	0.10685	0.02731	0.0101	1.0518
Factor8	0.07954	0.07914	0.0076	1.0593
Factor9	0.0004	0.00043	0	1.0593
Factor10	-0.00004	0.00011	0	1.0593
Factor11	-0.00015	0.02739	0	1.0593
Factor12	-0.02754	0.04573	-0.0026	1.0567
Factor13	-0.07327	0.05497	-0.007	1.0498
Factor14	-0.12824	0.03443	-0.0122	1.0376
Factor15	-0.16267	0.07057	-0.0154	1.0221
Factor16	-0.23324	.	-0.0221	1
LR test: independent vs. saturated: chi2(120) = 3.0e+05 Prob>chi2 = 0.0000				

We draw the screeplot curve, which shows in Fig.3. From Fig.3, we can see that only the first three factors are more significant than 1. Therefore, we choose factor 1, factor 2, and factor 3 as factors for further analysis.

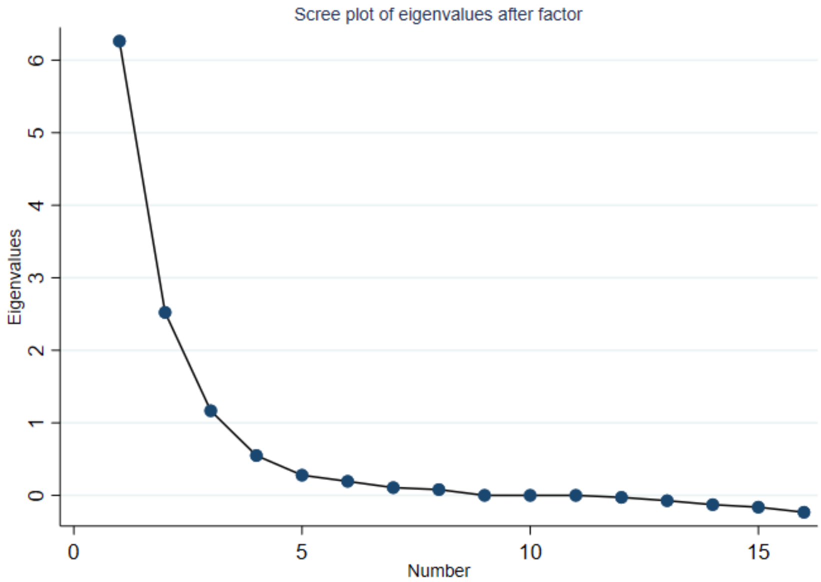

Figure 3: Screeplot

We rotate the results of factor analysis, and the results show that table11, table12, and Table13. From table 11, we can see that the cumulative variance of factor1, factor, and factor3 is 0.9353 after executing rotate, which has a better explanatory ability.

Table 11: Rotate results

Factor	Variance	Difference	Proportion	Cumulative
Factor1	4.95286	2.43954	0.4702	0.4702
Factor2	2.51332	0.12707	0.2386	0.7088
Factor3	2.38625	1.83592	0.2265	0.9353
Factor4	0.55033	0.19259	0.0522	0.9876
Factor5	0.35774	0.15946	0.034	1.0215
Factor6	0.19828	0.08303	0.0188	1.0404
Factor7	0.11526	0.031	0.0109	1.0513
Factor8	0.08426	0.08386	0.008	1.0593
Factor9	0.0004	.	0	1.0593
LR test: independent vs. saturated: chi2(120) = 3.0e+05 Prob>chi2 = 0.0000				

Table 12: Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9	Uniqueness
Followers	-0.0035	0.236	0.0144	0.0307	0.008	0.3154	0.0063	0.0277	0	0.8428
Frequency	0.0004	-0.0372	0.0029	0.0563	0.0055	-0.3032	-0.0032	0.0047	0	0.9034
Ave_forward	-0.0002	**0.7022**	-0.0028	0.0173	-0.0098	0.029	-0.0002	-0.1182	0	0.4917
Ave_vote	0.0011	**0.9122**	-0.0025	-0.0048	0.0032	-0.008	-0.0008	0.0419	0	0.166
Highest_vote	-0.0002	**0.7282**	0.0007	-0.0101	0.0034	0.0692	-0.0051	0.212	0	0.4199
Ave_comment	0	**0.7749**	-0.0016	0.0149	-0.0026	-0.0129	0.0052	-0.1504	0	0.3765
History_public	-0.0336	0.0173	-0.0205	0.5192	-0.0115	0.0136	0.0032	-0.0078	-0.0001	0.7282
Highest_public_perday	-0.0469	0.0006	-0.0098	0.5241	-0.0114	-0.0188	-0.007	0.005	0.0001	0.7225
Ave_vote_latest	0.373	-0.0015	**0.9274**	-0.0032	0.0281	0.0002	-0.0068	0.0003	-0.0047	0
Ave_comment_latest	0.866	-0.0036	0.446	-0.021	0.1025	0.0104	0.2032	-0.0051	-0.0099	-0.0013
Ave_forward_latest	**0.9858**	0.003	0.1276	-0.0045	-0.1036	-0.0001	-0.0582	0.0041	-0.0089	-0.0023
Highest_comment_latest	**0.6442**	-0.0013	0.4545	-0.0222	0.5036	0.0025	0.0228	0.0011	0	0.1237
Highest_forward_latest	**0.9018**	-0.0001	0.1657	-0.0036	0.2449	-0.0167	-0.1596	-0.0036	0.0005	0.0736
Total_comment_latest	**0.8659**	-0.0038	0.4466	-0.018	0.1	0.0098	0.2028	-0.0052	0.0102	-0.0009
Total_vote_latest	0.3727	-0.0015	**0.9275**	-0.0022	0.0271	-0.0004	-0.007	0.0004	0.0047	0
Total_forward_latest	**0.9858**	0.0027	0.1284	-0.0006	-0.1044	-0.001	-0.0567	0.0044	0.0084	-0.0026

We extract the variables with significant weight from factors factor1, factor2, and Factor3 in table12 and display the obtained variables in table 13. We can see that the first factor relates to the social efficiency of the last 30 days, which belongs to the recent social efficiency defined earlier, mainly including the forwarding and comment data of the previous 30 days. Then we extract the second factor. We can see that the second factor primarily relates to the historical social efficiency, so it is close to the historical social efficiency factor we defined. Finally, we extract the third factor, and we can see that the third factor focuses on the number of likes obtained in the last 30 days, which is also close to the recent social efficiency defined by us. Further, we can see that the results of factor analysis show that link width (for example, the number of fans) is not prominent in factor analysis; that is, the H1 hypothesis lacks support here.

Table 13: Factors

Factors	Factors name	Variables
Factor1	current_eff_part1	Ave_forward_latest Highest_comment_latest Highest_forward_latest Total_comment_latest Total_forward_latest
Factor2	his_eff	Ave_forward Ave_vote Highest_vote Ave_comment
Factor3	current_eff_part2	Ave_vote_latest Total_vote_latest

As can be seen from Table 14, the correlation between factor1, factor2, and Factor3 is low.

Table 14: Factor rotation matrix

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9
Factor1	0.8624	**-0.0021**	**0.4929**	-0.02	0.1108	0.0012	0.0262	-0.0005	0
Factor2	**0.0038**	0.9981	**-0.0018**	0.013	-0.0014	0.0598	-0.0001	0.0002	0
Factor3	**-0.5024**	**0.0029**	0.8587	0.0092	0.0767	0.0094	0.0645	-0.0002	0
Factor4	**0.0247**	**-0.011**	**0.0103**	0.9972	-0.0541	-0.0364	-0.0162	-0.0162	0.0001
Factor5	**-0.0561**	**0.0018**	**-0.1223**	0.0558	0.9891	-0.0186	0.009	0.0003	0.0004
Factor6	**-0.0043**	**0.0591**	**0.0162**	-0.0401	-0.0136	-0.9781	-0.089	-0.1729	0.0001
Factor7	**-0.0102**	**-0.003**	**0.0652**	-0.01	0.0179	0.0529	-0.9742	0.2084	-0.0001
Factor8	**0.0022**	**0.0109**	**-0.0106**	0.0117	-0.0074	-0.1877	0.1947	0.9625	0.0001
Factor9	**0**	**0**	**0**	0.0001	0.0004	-0.0001	0.0001	0	-1.0002

From table 15, we can see that the kmo value of all variables is more significant than 0.5.

Table 15: KMO result2 after removing low kmo variable

Variable	kmo
Followers	0.7803
Frequency	0.5299
Ave_forward	0.8748
Ave_vote	0.691
Highest_vote	0.754
Ave_comment	0.7874
History_public	0.5272
Highest_public_perday	0.5264
Ave_vote_latest	0.6242
Ave_comment_latest	0.6413
Ave_forward_latest	0.6781
Highest_comment_latest	0.8649
Highest_forward_latest	0.8813
Total_comment_latest	0.6414
Total_vote_latest	0.6236
Total_forward_latest	0.681
Overall	0.6977

We draw the factor-loading diagram, as shown in Fig.4. From Fig.4, we can see that the primary influence sources of factor1 and factor2 are quite different. The primary influence of factor1 comes from social behavior in the last 30 days, while the primary influence source of factor1 comes from the social performance of the whole history.

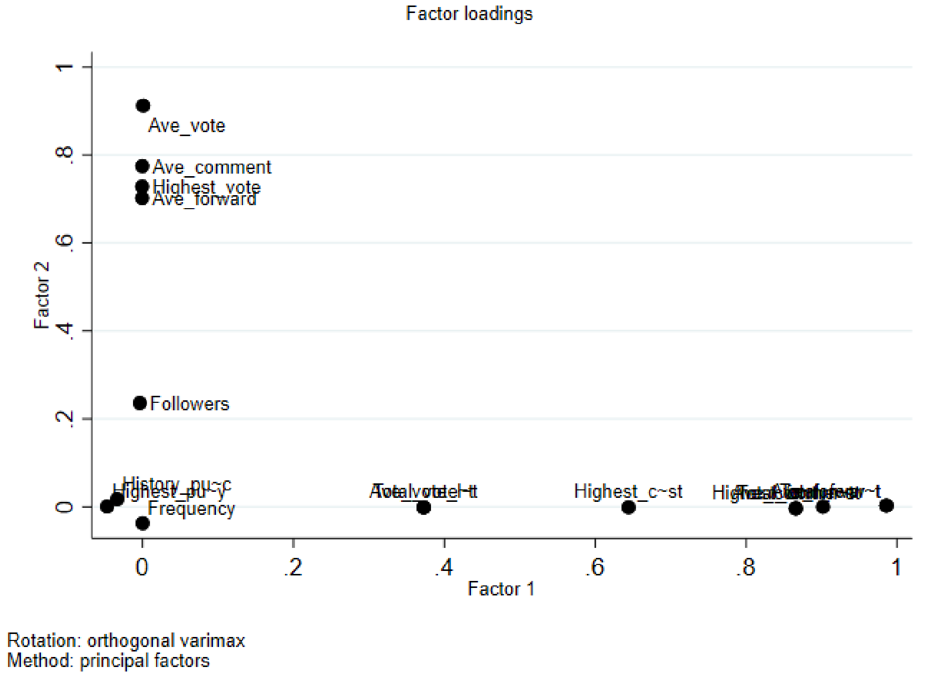

Figure 4: Factors loading

We predict F1, F2, and F3, and the results show in table 16

Table 16: The anticipated result of f1, f2, and f3

Variable	Factor1	Factor2	Factor3
Followers	-0.00184	0.02969	0.00038
Frequency	-0.00075	-0.00108	0.00026
Ave_forward	-0.00036	0.14513	-0.0006
Ave_vote	0.0006	0.56304	0.00194
Highest_vote	-0.00229	0.14332	0.00023
Ave_comment	0.00029	0.19427	0.00051
History_public	0.00039	0.00368	0.0038
Highest_public_perday	0.00486	-0.00339	-0.00404
Ave_vote_latest	-0.20546	-0.1424	0.65217
Ave_comment_latest	-0.51053	-0.1155	0.14342
Ave_forward_latest	0.63478	0.14734	-0.24389
Highest_comment_latest	0.11641	0.00893	-0.07146
Highest_forward_latest	-0.01175	-0.01047	-0.02581
Total_comment_latest	0.72505	0.09285	-0.2262
Total_vote_latest	-0.07212	0.1495	0.54793
Total_forward_latest	0.23146	-0.12647	-0.06674

We draw the scoreplot graph in Fig.5. As can be seen from Fig.5, the data points mainly concentrated within 10.

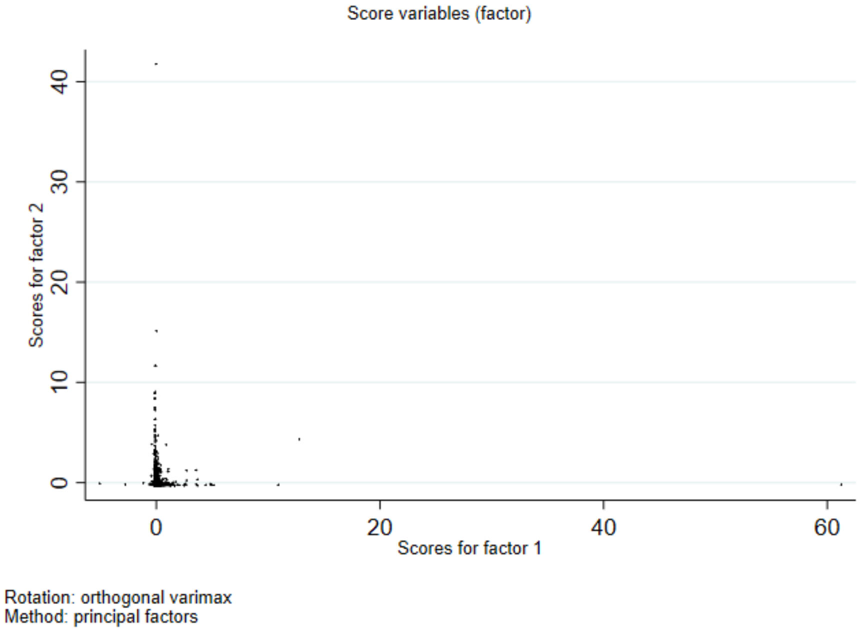

Figure 5: Scoreplot

We drew the score plot again in the range of (1,1). In Figure 6, we can see some differences in the distribution of factor1 and factor2.

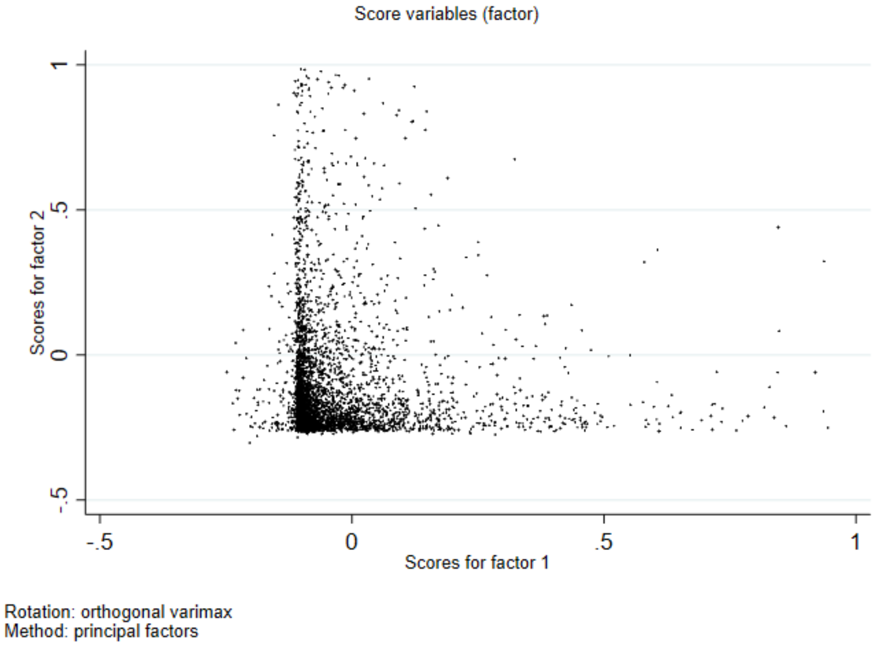

Figure 6: Scoreplot for a specific range

We further analyzed the correlation between F1, F2, and F3, and the results show in Table 17. From Table 17, we can confirm that F2, F2, and F3 have little correlation.

Table 17: Correlation of f1, f2, and f3

	f1	**f2**	**f3**
f1	1		
f2	0.0004	1	
f3	0.0003	-0.0002	1

4.3.2 OLS regression

We put F1, F2, and F3 together with other variables that affect pricing into the model, analyze the relationship between factors and KOL transaction price, and the regression results show in table 18. As can be seen from table 18, F2 has a significant positive correlation with the trading price of KOL, which means that the higher the historical social efficiency is, the higher the trading price of KOL is. In the ordinary OLS regression results, F1 and F3 have no significant relationship with KOL's transaction price. Still, in the robustness test, we can see that there is a negative correlation (-491.5) between F3 and KOL's transaction price, which means that the social efficiency (average and highest praise data obtained) in the last 30 days has a negative correlation with KOL's transaction price. At the same time, the empirical results show that the H3 hypothesis is not supported.

Besides, the robustness test results ((robust cluster regression)) show that if KOL's identity is a singer, then KOL's transaction price will drop significantly (-18,313). Similarly, if KOL's identity is multiple, KOL's transaction price will dramatically drop (- 12,849).

Compared with the KOL transaction with the trade type of produce, the KOL transaction price with the trade mode of forwarding decreased significantly (-6,725).

Compared with the Ad_and_marketing industry, KOL transaction price of the car industry (13,125), the handmade industry (35,302), the internet industry (40718), the news and info industry(8,389) is significantly higher. In contrast, the KOL transaction price in the health (-8,012) industry is considerably lower.

Compared with the Anhui province, the KOL transaction prices in Beijing (8,214), Shanghai (12,276), Taiwan (10,439), and Zhejiang (11,938) are significantly higher, while those in Hainan (-6,339) and Heilongjiang (-4,276) are substantially lower. In a word, the KOL's transaction price tends to be higher in economically developed regions and lower in more remote and underdeveloped areas.

Table 18: Regression results

	(1)	(2)	(3)	(4)
	Without f2 and f3	**Without f3**	**All factors**	**Robust Check**
VARIABLES	Price	Price	Price	Price
f1	115.1	81.53	82.41	82.41
	(532.2)	(515.9)	(515.9)	(259.9)
f2		12,870***	12,868***	12,868***
		(549.6)	(549.6)	(3,380)
f3			-491.5	-491.5*
			(512.8)	(265.1)
Public_figure==1	-4,463	-2,934	-2,948	-2,948
	(10,730)	(10,401)	(10,401)	(3,013)
Public_figure==2	-2,653	-2,848	-2,766	-2,766
	(10,529)	(10,206)	(10,207)	(2,478)

Public_figure==3	-18,830	-18,277	-18,313	-18,313***
	(34,846)	(33,777)	(33,777)	(3,861)
Public_figure==4	-12,598	-12,832	-12,849	-12,849**
	(36,787)	(35,658)	(35,659)	(6,309)
Trade_type==forward	-6,839***	-6,728***	-6,725***	-6,725***
	(1,060)	(1,027)	(1,027)	(979.2)
Industry_type==Beauty_makeup	4,771	1,162	1,204	1,204
	(11,758)	(11,398)	(11,398)	(4,391)
Industry_type==Campus	2,349	-2,371	-2,320	-2,320
	(12,296)	(11,920)	(11,920)	(4,604)
Industry_type==Car	13,263	13,113	13,125	13,125**
	(12,064)	(11,694)	(11,694)	(5,118)
Industry_type==Constellation	-1,955	-3,552	-3,489	-3,489
	(13,234)	(12,828)	(12,829)	(4,411)
Industry_type==Culture	2,807	-7,173	-7,186	-7,186
	(18,387)	(17,828)	(17,828)	(7,320)
Industry_type==Digital	-2,884	-2,594	-2,601	-2,601
	(12,215)	(11,840)	(11,840)	(4,261)
Industry_type==E-commerce	-4,777	-5,456	-5,420	-5,420
	(23,121)	(22,412)	(22,412)	(4,442)
Industry_type==Education	-470.0	-1,967	-1,963	-1,963
	(13,794)	(13,371)	(13,371)	(5,258)
Industry_type==Emotion_sentiment	7,236	4,770	4,845	4,845
	(11,716)	(11,357)	(11,358)	(4,956)
Industry_type==Entertainment	-2,497	-5,460	-5,437	-5,437
	(11,733)	(11,374)	(11,374)	(4,370)
Industry_type==Fashion	1,833	-35.31	-15.50	-15.50
	(11,706)	(11,347)	(11,347)	(4,368)
Industry_type==Film_and_TV	-915.5	-4,038	-4,015	-4,015
	(11,804)	(11,443)	(11,443)	(4,352)
Industry_type==Finance_and_Economics	14,481	14,024	14,043	14,043
	(12,287)	(11,910)	(11,910)	(12,499)
Industry_type==Food	8,335	3,950	3,975	3,975
	(11,806)	(11,445)	(11,445)	(4,910)
Industry_type==Fun_and_Joke	3,384	-4,145	-3,982	-3,982
	(12,058)	(11,693)	(11,694)	(4,928)
Industry_type==Game	5,243	3,527	3,534	3,534
	(11,935)	(11,569)	(11,570)	(5,572)
Industry_type==Gymnastic	-2,735	-2,408	-2,375	-2,375
	(12,600)	(12,213)	(12,213)	(4,370)
Industry_type==Handmade	51,081	35,377	35,302	35,302***
	(36,690)	(35,570)	(35,570)	(10,407)
Industry_type==Health	-3,732	-8,022	-8,012	-8,012*
	(16,607)	(16,098)	(16,098)	(4,713)
Industry_type==Home_furnishing	-4,303	-4,495	-4,559	-4,559
	(12,949)	(12,552)	(12,552)	(4,313)
Industry_type==Internet	42,201***	40,358***	40,718***	40,718**
	(12,704)	(12,315)	(12,320)	(16,571)
Industry_type==Life	6,852	5,138	5,152	5,152
	(12,360)	(11,981)	(11,981)	(5,253)

Industry_type==Literature_and_art	-1,470	-4,621	-4,596	-4,596
	(12,627)	(12,240)	(12,240)	(4,735)
Industry_type==Military	-872.8	-3,489	-3,467	-3,467
	(12,941)	(12,545)	(12,545)	(4,572)
Industry_type==Mother_and_infant	6,561	4,293	4,327	4,327
	(11,844)	(11,481)	(11,481)	(5,847)
Industry_type==Music	-5,071	-5,635	-5,610	-5,610
	(19,418)	(18,823)	(18,823)	(4,583)
Industry_type==News_and_Info	9,938	8,353	8,389	8,389*
	(11,693)	(11,334)	(11,335)	(4,474)
Industry_type==Other	3,221	1,090	1,157	1,157
	(11,630)	(11,273)	(11,273)	(4,336)
Industry_type==Outdoor	-5,517	-5,130	-5,148	-5,148
	(36,554)	(35,432)	(35,432)	(4,811)
Industry_type==Pets	-2,139	-6,673	-6,696	-6,696
	(14,750)	(14,299)	(14,299)	(4,683)
Industry_type==Sports	3,861	4,032	4,028	4,028
	(14,633)	(14,184)	(14,184)	(6,185)
Industry_type==Technology	105.5	-1,365	-1,352	-1,352
	(13,269)	(12,862)	(12,862)	(5,261)
Industry_type==Travel	1,309	-361.8	-331.8	-331.8
	(12,027)	(11,658)	(11,658)	(4,373)
District==Beijing	10,134	8,149	8,214	8,214***
	(10,336)	(10,020)	(10,020)	(2,281)
District==Chongqing	1,884	1,223	1,267	1,267
	(11,619)	(11,262)	(11,262)	(2,628)
District==Fujian	2,846	760.9	804.7	804.7
	(10,939)	(10,604)	(10,604)	(2,407)
District==Gansu	-3,095	3,226	3,103	3,103
	(26,759)	(25,939)	(25,939)	(3,421)
District==Guangdong	3,983	103.9	229.2	229.2
	(10,405)	(10,087)	(10,088)	(2,251)
District==Guangxi	-1,198	-1,316	-1,312	-1,312
	(15,091)	(14,628)	(14,628)	(3,429)
District==Guizhou	2,163	2,533	2,552	2,552
	(22,807)	(22,107)	(22,107)	(5,340)
District==Hainan	-6,289	-6,343	-6,339	-6,339**
	(18,615)	(18,044)	(18,044)	(2,653)
District==Hebei	2,511	-377.7	-334.2	-334.2
	(13,365)	(12,955)	(12,955)	(2,448)
District==Heilongjiang	-3,482	-4,390	-4,276	-4,276*
	(14,832)	(14,377)	(14,377)	(2,463)
District==Henan	-1,663	-766.8	-762.4	-762.4
	(11,742)	(11,382)	(11,382)	(1,994)
District==Hongkong	3,456	3,409	3,419	3,419
	(12,534)	(12,150)	(12,150)	(2,591)
District==Hubei	-447.5	-2,718	-2,697	-2,697
	(11,479)	(11,127)	(11,127)	(2,488)
District==Hunan	2,936	1,441	1,497	1,497
	(11,580)	(11,225)	(11,225)	(3,518)
District==Jiangsu	1,382	35.73	60.84	60.84

	(10,706)	(10,378)	(10,378)	(1,956)
District==Jiangxi	-6,311	-6,406	-6,444	-6,444
	(14,087)	(13,655)	(13,655)	(4,469)
District==Jilin	-305.5	-1,485	-1,450	-1,450
	(14,349)	(13,909)	(13,909)	(3,269)
District==Liaoning	343.3	199.5	219.1	219.1
	(11,737)	(11,377)	(11,377)	(1,993)
District==Macao	26.02	-5,320	-5,291	-5,291
	(15,560)	(15,084)	(15,084)	(3,744)
District==Nationwide	7,570	6,174	6,229	6,229***
	(10,300)	(9,985)	(9,985)	(1,976)
District==Neimenggu	-8,832	-8,686	-8,688	-8,688*
	(22,566)	(21,873)	(21,873)	(5,082)
District==Ningxia	3,151	1,743	1,767	1,767
	(36,237)	(35,125)	(35,125)	(3,054)
District==Other	10,270	7,144	7,154	7,154***
	(10,554)	(10,231)	(10,231)	(2,539)
District==Overseas	7,222	3,965	3,991	3,991
	(10,445)	(10,126)	(10,126)	(2,622)
District==Shandong	2,371	1,648	1,714	1,714
	(11,355)	(11,007)	(11,007)	(2,694)
District==Shanghai	14,668	12,259	12,276	12,276***
	(10,443)	(10,123)	(10,124)	(2,896)
District==Shanxi	1,650	96.88	119.3	119.3
	(13,868)	(13,443)	(13,443)	(2,319)
District==Shanxi_1	12,624	10,903	10,931	10,931
	(12,652)	(12,264)	(12,264)	(10,074)
District==Sichuan	7,504	4,675	4,687	4,687
	(11,069)	(10,730)	(10,730)	(2,945)
District==Taiwan	10,309	10,407	10,439	10,439**
	(15,794)	(15,309)	(15,309)	(4,627)
District==Tianjin	9,572	9,450	9,459	9,459
	(12,729)	(12,339)	(12,339)	(6,631)
District==Yunnan	-2,927	-2,294	-2,294	-2,294
	(13,272)	(12,865)	(12,865)	(2,552)
District==Zhejiang	14,393	11,805	11,938	11,938***
	(10,859)	(10,526)	(10,527)	(3,288)
Constant	3,476	7,828	7,730	7,730*
	(15,477)	(15,004)	(15,004)	(4,673)
Observations	8,585	8,585	8,585	8,585
R-squared	0.024	0.083	0.083	0.083

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.3.3 Heterogeneity

Because different KOLs have different numbers of fans, different amounts of fans may lead to different transaction prices of KOL. We grouped KOL according to the number of fans and then made a robust regression for each group. The results show in Table 19.

As can be seen from table 19, for KOL with more than 500000 fans, the transaction price of F3 and KOL significantly positively correlated. At the same time, that of F1 and F2 shown no correlations with that of KOL.

For KOL with 100000-500000 fans, F1 and F2 positively correlate with KOL's transaction price (1,475 and 10,690).

For KOL with less than 100000 fans, the transaction price of F2 and KOL is significantly positively correlated (22,436), but the transaction price of F1 and KOL is significantly negatively correlated (-2,983).

The results of the heterogeneity analysis show that there is a significant positive correlation between KOL's historical social efficiency and KOL's transaction price. However, for KOL with a low number of fans, if the social efficiency is too high in the last 30 days, it will lead to a decrease in KOL's transaction price.

For KOL with followers>1000000, compared with other identities, there is a significant negative correlation between the actor's identity and the KOL's transaction price (-8,452).

For KOL with followers>500000 & followers<1000000, there is a significant negative correlation between the host's identity and the transaction price (-6,053).

For KOL with followers>100000 & followers<500000, there was a significant positive correlation between the host's identity and the transaction price (17,493). For KOL with followers<100000, there was a significant positive correlation between the singer's identity and KOL's transaction price (2,285).

When a KOL has multiple identities and the number of fans exceeds 1 million, there is a negative correlation between the various identities and the transaction price (- 16,040).

For KOL with more than 100000 fans, compared with the trade mode with trade type of produce, if the trade mode is forward, the price will drop significantly.

For KOL with followers>1000000, only handmade (27,990) industry and Internet (70,242) industry have significantly higher KOL transaction prices, compared with AD and marketing industry, while other industries have no significant difference.

For KOL with followers>500000 & followers<1000000, the transaction price of is significantly higher than that of Ad_and_marketing in the following industries: Beauty_makeup (8,783), Car (14,709), Digital (12,210), Education (6,971), Emotion_sentient (7,927), Fashion (3,289), Finance_and_economics (9,584), Fund_and_joke (6,331), Game (5,345), Literature_and_art (5,921),Military(3,618), Mother_and_infant (5,749), News_and_Info (3,953), travel (6,424), etc., While the KOL transaction price of Pets (-4,709) industry is significantly lower.

For KOL with followers>100000 & followers<500000, the transaction price of KOL is significantly lower than that of Ad_and_marketing in the following industries: Car (-12,350), E-commerce (-123,71), Education(-11,245), Finance_and_economics (-11,735), Fund_and_join (-11,515), Gymnastic (-11,739), Home_financing (- 12,319), News_and_info (-11,179), Pets(-11,999),Technology(-12,360),etc.

For KOL with followers<100000, the transaction price of KOL is significantly lower in the culture (-8,684) industry, while the transaction price is significantly higher ins: Beauty_makeup (2,664), Campus (1,436), Emotion_sentiment (1,219), Fashion (714.4), Technology(1,802) and Travel (2,097), Mother_and_infant (3,447), Film_and_TV(1,598), Outdoor(2,008), Game(2,664), Finance_and_Economics (1,303), Fun_and_Joke (6,961), News_and_Info (6,794), Literature_and_art (4,485), etc.

In terms of regional differences, for KOL with followers>1000000, compared with Anhui, in developed regions, such as Beijing, Shanghai, overseas, Hongkong, Guangdong, Zhejiang, Tianjin, and Taiwan, the transaction price of KOL is significantly higher. Simultaneously, in regions and provinces with a large population, such as Hunan, Sichuan, Henan, and Hebei, KOL's transaction price is significantly higher. It is also markedly higher in Ningxia.

For KOL with followers>500000 & followers<1000000, compared with Anhui, the trading price of KOL in Guizhou, Shangxi, and Shanxi is significantly higher, while the trading price of KOL in

Hebei and Macao is considerably lower;

For KOL with followers>100000 & followers<500000, compared with Anhui, the trading price of KOL in Guangdong, Guangxi, Liao Ning, Henan, Hunan, Hubei, Jiangsu, Macau, Liao Ning, Yun, Tianjin, Shanxi, Shanxi, and other regions is relatively low.

For KOLs with followers<100000, comparing with Anhui, the KOL transaction price in Guangdong and Guangxi regions is significantly higher, while the KOL transaction price is considerably lower in Hebei and Sichuan.

Table 19: The heterogeneity of regression results caused by the number difference of followers

	(1)	(2)	(3)	(4)	(5)
	All	Followers >1000000	Followers>500000 & Followers<1000000	Followers>100000& Followers<500000	Followers <100000
VARIABLES	Price	Price	Price	Price	Price
f1	82.41	204.2	-469.8	1,475**	-2,983*
	(259.9)	(337.8)	(396.1)	(750.4)	(1,532)
f2	12,868***	12,352***	12,082***	10,690***	22,436**
	(3,380)	(3,387)	(3,958)	(3,801)	(10,880)
f3	-491.5*	-124.9	-19.84	-45.38	60.27
	(265.1)	(432.9)	(105.0)	(216.7)	(468.8)
Public_figure==1	-2,948	-6,359	-6,053**	17,493***	
	(3,013)	(4,916)	(2,784)	(6,237)	
Public_figure==2	-2,766	-8,452**	-401.0	-4,918	3.178
	(2,478)	(3,768)	(4,911)	(6,561)	(780.3)
Public_figure==3	-18,313***				2,285***
	(3,861)				(298.3)
Public_figure==4	-12,849**	-16,040**			
	(6,309)	(7,852)			
Trade_type==forward	-6,725***	-9,133***	-3,909***	-1,741***	-285.7
	(979.2)	(1,502)	(1,034)	(665.5)	(658.1)
Industry_type==Beauty_makeup	1,204	-2,417	8,783***	-10,412	2,664***
	(4,391)	(10,156)	(1,836)	(6,390)	(748.5)
Industry_type==Campus	-2,320	-6,395	1,550	-9,613	1,436*
	(4,604)	(10,611)	(3,859)	(6,457)	(850.1)
Industry_type==Car	13,125**	15,305	14,709***	-12,350*	-69.10
	(5,118)	(10,849)	(3,327)	(6,410)	(194.1)
Industry_type==Constellation	-3,489	-8,722	62.38	-2,698	
	(4,411)	(9,972)	(1,442)	(7,900)	
Industry_type==Culture	-7,186	-15,018			-8,684***
	(7,320)	(12,397)			(1,894)
Industry_type==Digital	-2,601	-8,714	12,210***	-10,126	330.7
	(4,261)	(9,956)	(3,516)	(6,442)	(367.5)
Industry_type==E-commerce	-5,420	-10,201	833.4	-12,371*	
	(4,442)	(10,548)	(1,895)	(6,436)	
Industry_type==Education	-1,963	-7,615	6,971**	-11,245*	
	(5,258)	(10,736)	(3,187)	(6,449)	
Industry_type==Emotion_sentiment	4,845	3,131	7,927***	-7,381	1,219***
	(4,956)	(10,873)	(2,004)	(6,692)	(389.1)
Industry_type==Entertainment	-5,437	-11,393	744.0	-7,913	411.1
	(4,370)	(10,025)	(1,167)	(6,888)	(371.5)
Industry_type==Fashion	-15.50	-3,840	3,289**	-10,291	714.4***
	(4,368)	(10,070)	(1,605)	(6,428)	(272.6)
Industry_type==Film_and_TV	-4,015	-10,944	6,428	-6,873	1,598***
	(4,352)	(10,027)	(4,169)	(6,653)	(492.5)
Industry_type==Finance_and_Economics	14,043	28,105	9,584***	-11,735*	1,303*
	(12,499)	(27,543)	(3,199)	(6,413)	(748.8)
Industry_type==Food	3,975	2,086	6,370**	-10,964*	731.8
	(4,910)	(10,592)	(3,072)	(6,390)	(454.0)

Industry_type==Fun_and_Joke	-3,982	-9,258	6,331*	-11,515*	6,961*
	(4,928)	(10,536)	(3,264)	(6,385)	(3,696)
Industry_type==Game	3,534	2,472	5,345***	-10,268	2,467***
	(5,572)	(11,546)	(1,474)	(6,432)	(752.5)
Industry_type==Gymnastic	-2,375	-7,090	79.39	-11,739*	-3,682
	(4,370)	(10,052)	(2,550)	(6,421)	(2,841)
Industry_type==Handmade	35,302***	27,990**			
	(10,407)	(13,640)			
Industry_type==Health	-8,012*	-11,990			-8,605
	(4,713)	(10,328)			(6,139)
Industry_type==Home_furnishing	-4,559	-8,844	-16.46	-12,319*	
	(4,313)	(10,065)	(1,945)	(6,419)	
Industry_type==Internet	40,718**	70,242**	2,041	-9,777	525.6
	(16,571)	(29,291)	(1,585)	(6,618)	(328.4)
Industry_type==Life	5,152	-323.1	125.8	3,533	-148.9
	(5,253)	(10,693)	(3,081)	(10,851)	(350.2)
Industry_type==Literature_and_art	-4,596	-12,460	5,921**	-6,811	4,485**
	(4,735)	(10,395)	(2,831)	(6,518)	(2,256)
Industry_type==Military	-3,467	-10,990	3,618*	4,131	
	(4,572)	(10,114)	(2,149)	(11,015)	
Industry_type==Mother_and_infant	4,327	3,183	5,749***	-10,850*	3,447*
	(5,847)	(11,837)	(2,179)	(6,404)	(1,773)
Industry_type==Music	-5,610	-11,533			
	(4,583)	(10,247)			
Industry_type==News_and_Info	8,389*	6,594	3,953***	-11,179*	6,794*
	(4,474)	(10,106)	(1,490)	(6,409)	(3,999)
Industry_type==Other	1,157	-2,984	6,866***	-8,002	2,655***
	(4,336)	(10,042)	(1,742)	(6,467)	(537.9)
Industry_type==Outdoor	-5,148				2,008***
	(4,811)				(154.0)
Industry_type==Pets	-6,696	-10,863	-4,709**	-11,999*	
	(4,683)	(10,183)	(2,231)	(6,274)	
Industry_type==Sports	4,028	-972.7	-1,924	-10,315	26,226**
	(6,185)	(12,060)	(2,081)	(6,473)	(12,195)
Industry_type==Technology	-1,352	-8,466	38,784	-12,360*	1,802**
	(5,261)	(10,844)	(25,448)	(6,411)	(819.6)
Industry_type==Travel	-331.8	-3,723	6,424**	-8,255	2,097***
	(4,373)	(10,168)	(2,650)	(6,519)	(694.3)
District==Beijing	8,214***	14,774***	-316.7	85.56	-1,197
	(2,281)	(2,960)	(3,121)	(1,142)	(1,017)
District==Chongqing	1,267	5,800	3,265	-2,470	874.2
	(2,628)	(4,191)	(4,981)	(1,575)	(770.3)
District==Fujian	804.7	4,245	3,032	-957.8	-405.9
	(2,407)	(2,954)	(7,352)	(1,117)	(789.9)
District==Gansu	3,103		-5,837		
	(3,421)		(3,960)		
District==Guangdong	229.2	4,615*	-2,947	-3,754***	2,139**
	(2,251)	(2,805)	(3,207)	(1,138)	(877.7)
District==Guangxi	-1,312	-71.24	-4,687	-3,794**	11,926***
	(3,429)	(5,747)	(3,999)	(1,614)	(1,831)
District==Guizhou	2,552	-4,617	20,171***	-947.3	
	(5,340)	(5,898)	(4,518)	(1,010)	
District==Hainan	-6,339**	-3,554		-1,331	
	(2,653)	(4,070)		(1,035)	
District==Hebei	-334.2	6,859*	-6,949*	-1,375	-1,706*
	(2,448)	(3,538)	(3,863)	(1,183)	(972.6)
District==Heilongjiang	-4,276*	-6,277	-5,297	-1,031	
	(2,463)	(5,961)	(3,547)	(1,014)	
District==Henan	-762.4	6,980**	-3,973	-2,252**	-1,587
	(1,994)	(2,807)	(3,223)	(994.6)	(2,094)
District==Hongkong	3,419	8,658***			

	(2,591)	(3,094)			
District==Hubei	-2,697	-1,466	-17.32	-1,933*	1,353
	(2,488)	(3,832)	(3,758)	(1,017)	(839.3)
District==Hunan	1,497	7,746*	-206.6	-2,390**	3,733
	(3,518)	(4,681)	(5,449)	(1,069)	(2,884)
District==Jiangsu	60.84	4,463	-3,774	-2,038**	-3,097
	(1,956)	(2,724)	(3,061)	(999.6)	(2,527)
District==Jiangxi	-6,444	-11,214	-4,776	-1,698	
	(4,469)	(9,858)	(3,550)	(1,106)	
District==Jilin	-1,450	3,029	-1,065	187.5	
	(3,269)	(4,021)	(4,234)	(1,691)	
District==Liaoning	219.1	3,525	4,108	-3,000***	-915.6
	(1,993)	(2,911)	(3,751)	(970.7)	(1,262)
District==Macao	-5,291	200.6	-8,580**		
	(3,744)	(4,484)	(3,870)		
District==Nationwide	6,229***	15,157***	967.8	781.2	1,197
	(1,976)	(2,990)	(3,200)	(889.7)	(732.3)
District==Neimenggu	-8,688*	-3,302	-5,561		
	(5,082)	(5,930)	(3,890)		
District==Ningxia	1,767	9,515**			
	(3,054)	(4,112)			
District==Other	7,154***	13,133***	1,102	-1,462	3,177*
	(2,539)	(3,175)	(3,938)	(1,272)	(1,744)
District==Overseas	3,991	8,207**	3,178	399.9	-146.4
	(2,622)	(3,245)	(4,610)	(1,496)	(935.9)
District==Shandong	1,714	4,225	8,922	-1,465	-2,981
	(2,694)	(4,008)	(7,837)	(1,152)	(2,534)
District==Shanghai	12,276***	21,278***	2,212	23.85	-315.8
	(2,896)	(4,185)	(3,697)	(1,190)	(867.3)
District==Shanxi	119.3	5,056*	10,265**	-10,254*	-1,208
	(2,319)	(2,966)	(4,028)	(5,428)	(807.0)
District==Shanxi_1	10,931	19,942	4,459	-2,797*	
	(10,074)	(14,130)	(4,955)	(1,541)	
District==Sichuan	4,687	11,594**	181.4	-315.7	-6,769*
	(2,945)	(4,739)	(3,630)	(1,389)	(3,714)
District==Taiwan	10,439**	15,501***		16,588	
	(4,627)	(4,225)		(18,277)	
District==Tianjin	9,459	18,278**		-3,027***	
	(6,631)	(9,072)		(1,090)	
District==Yunnan	-2,294	-24.38	-5,038	-2,672*	-597.1
	(2,552)	(6,631)	(3,655)	(1,498)	(740.3)
District==Zhejiang	11,938***	20,612***	6,906	-803.8	903.3
	(3,288)	(4,758)	(4,946)	(1,899)	(688.3)
o.Public_figure==3		-	-	-	
o.Industry_type==Outdoor		-	-	-	
o.District==Gansu		-		-	-
o.Public_figure==4			-	-	-
o.Industry_type==Culture			-	-	
o.Industry_type==Handmade			-	-	-
o.Industry_type==Health			-	-	
o.Industry_type==Music			-	-	-
o.District==Hainan			-		-

o.District==Hongkong			-	-	-
o.District==Ningxia			-	-	-
o.District==Taiwan			-		-
o.District==Tianjin			-		-
o.District==Macao				-	-
o.District==Neimenggu				-	-
o.Public_figure==1					-
o.Industry_type==Constellation					-
o.Industry_type==E-commerce					-
o.Industry_type==Education					-
o.Industry_type==Home_furnishing					-
o.Industry_type==Military					-
o.Industry_type==Pets					-
o.District==Guizhou					-
o.District==Heilongjiang					-
o.District==Jiangxi					-
o.District==Jilin					-
o.District==Shanxi_1					-
Constant	7,730*	8,171	4,768	16,544**	4,689*
	(4,673)	(10,204)	(3,461)	(6,538)	(2,656)
Observations	8,585	5,421	1,195	1,503	466
R-squared	0.083	0.094	0.086	0.072	0.213

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

5. Conclusions

This paper discusses the identification, valuation, and pricing of digital social assets. In this paper, we propose that core and non-core factors affect the value and price of digital social assets, and we then conduct an empirical test based on KOL's trading data.

We found that the historical social efficiency is the core factor affecting the transaction price of digital social assets. There is a significant positive correlation between the historical social efficiency and the transaction price of digital social assets. However, the recent social efficiency factor has the opposite effect. In the robustness test, we found that the current social efficiency factor has a significant negative correlation with the transaction price of digital social assets.

Furthermore, we find that the following differences will lead to the heterogeneity of transaction prices of digital social assets: the number of fans owned by social entities, industry differences, regional or provincial differences, etc.

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