"Does internet usage activate or inactivate global stock markets? Exploration by spatial econometrics models"

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SECTION 1. Macroeconomic processes and regional economies management

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Does internet usage activate or inactivate global stock markets? Exploration by spatial econometrics models

Abstract

Does internet usage activate or inactivate stock markets? On one hand, the vast and quick online information flow forces investors to trade more frequently. On the other hand, information overflow makes them anxious and shying away from decision making, thus hinders trading. This is the first paper to examine the internet effects on stock trading in 30 markets globally by spatial panel models. Empirical results indicate negative internet effects on stock trading. As a whole, internet usages hinder, rather than facilitate, stock trading. In addition, global stock trading demonstrates highly significant spatial correlations; spatial econometric models are more appropriate than OLS models in exploring global stock issues.

Keywords: internet usage, global stock market, spatial correlations.
JEL Classification: F39, G15.

Introduction

Following the development of web2.0, it is much easier to get information than ever before for stock investors. The widespread usage of internet has impacted business and trading models greatly. Over internet stock investors now can make trading within seconds. Most importantly, it is much easier for them to gather information and reduce uncertainty. As a result, investors trade more (Barber and Odean, 2002) and trade more frequently (Choi, Laibson, and Metrick, 2002). Stock markets turn out to be more active with internet usage, according to financial economists.

From the perspectives of communication and sociology, on the other hand, the side effects of vast online information have obviously emerged. Anxiety, instead of joyfulness, starts to dominate the feeling of internet users in handling online information. Several phrases are used to describe it, such as information overload (Kock, 2000), information anxiety (McCarthy, 1991), and information apprehension (Susskind & Stephanone, 2000), etc. The anxiety or apprehension might prohibit investors from making decisions, rather than foster them. We observe that scholars from different tracks hold different, if not opposite, arguments toward the influences of vast online information. Whether the rapid growth in internet usage activates or inactivates financial markets remains an issue to explore.

In addition, spatial associations, the correlations among neighboring areas, are often significant in the issues involving interaction or co-movement among units. Various factors could result in spatial correlations, such as weather, culture, distance, historical events, etc. Whatever the factors are, the estimates in regression models may be biased and lead to misjudgments if significant spatial correlations are neglected. To avoid the bias, we apply spatial econometrics models to examine the internet effects on global stock markets. It would effectively reduce estimation errors and offer us a clearer picture about how internet usage impacts global stock markets.

Our empirical results come up with a different viewpoint from the financial main stream. We find pervasively negative internet effects on global stock trading. Internet usage hinders stock trading. As for the spatial correlation, without surprising, it plays a very influential role in global stock market; stock markets intertwine with neighboring countries.

The next section is a literature review, followed by the introduction of methodology. Then is the report and interpretation of empirical results. The last section concludes this paper.

1. Literature review

The easiness and convenience of using internet to gather information and make transaction have fostered stock investors to trade (Barber and Odean, 2002), and lead to higher trading volume reactions that are unrelated to price change (Anwers, Schneible, Jr., and Stevens, 2003). Barber and Odean (2002) investigate 1,607 investors switching from phone-based to online trading during the

1990s, and find them trading more actively, more speculatively, and less profitably after going online. Choi, Laibson, and Metrick (2002) analyze the impact of a web-based trading channel on traders' behavior and performance in two large corporate 401(k) plans. After 18 months of Web access, the trading frequency at web-based firms is the double of the control group without Web channels.

To financial economists, the benefits and contributions of e-communication are of no question, since information is the best vehicle to reduce perceived risk. However, when information overwhelms, it could cause impediment, instead of facilitation, to trading activity, either due to information overload, information anxiety or information apprehensiveness. According to Kock (2000), information overload is associated with a feeling of inability to handle a given amount of information to carry out activities, which implies excessive burdens and a loss-of-control sense. Information anxiety was defined as a ''kind of stupor, a feeling that we simply can't keep up, can't read fast enough, don't know how to locate the information we need, don't have time to sort through or think about all the data surrounding us'' (McCarthy, 1991, p. 12). This feeling also happens on internet, known as internet apprehensiveness. Internet apprehensiveness has been tapped in many aspects, such as self-efficacy (Eastin and LaRose, 2000), retail purchasing (Susskind and Stephanone, 2000), interpersonal relationships (Clarke, 1991; Flaherty, Pearce, and Rubin, 1998) and education (Brown and Vician, 1995; Bohlin and Hunt, 1995; Presno, 1998). Most important among them to this paper is Susskind's (2001) finding that internet apprehensiveness associates positively with on-line information seeking behaviors.

In sum, information reduces uncertainty and benefits decision making. However, when faced with information floods, one may turn into escaping from decision making, since one's attention span is limited and can focus only on a few things. If this happens in a stock market, we will see the market more sluggish, instead of more active. Hence, whether the fast-growing online information activates or hinders stock trading remains to be further studied. We will examine the internet effects, with the consideration of spatial association.

Next section will introduce the spatial correlation models.

2. Spatial correlation models

Ever since the stock market crash in 1987, many people have noticed the co-movement among global stock markets getting higher. The correlations among global stock markets have significantly increased over past years; the global average of correlation coefficients of stock trading between pair countries increased from 0.21 in 1999 to 0.30 in 2006 (Kuo and Wu, 2008). The dyad correlations are various; some are higher, some are lower; and some are positive, some are negative. A few factors may cause the variance, such as distance (Portes and Rey, 2005; Portes and Rumbaut, 2001; Hilliard, 1979), graphical adjacency (Thomas, Flavin, Margaret, Hurley and Fabrice, 2001), same or different languages (Forbes, 1993), length of market opening overlap (Flavin, Hurley and Roursseau, 2001; Portes and Rey, 2005), time length of phone calls (Portes and Rey, 2005), etc. These factors all imply that, explicitly or implicitly, spatial factors are important in cross-nations stock trading.

To examine how the internet usage impacts international stock markets, we collect stock trading data in 30 countries from 1999 to 2004, build a basic panel model, and adopt Hausman test to find out which model, fixed effects model (FE) or random effects model (RE), fits the data best. If random effect model is rejected and country-specific fixed effect fits better, we need to consider spatial associations. We examine the spatial effects and analyze the internet effect on stock trading by constructing both spatial lagged model and spatial error model. (See the Appendix for details.)

2.1. Panel regression model. To examine the internet effect, the basic panel regression model is as follows

$$y_{it} = \alpha_i + X_{it}B + \varepsilon_{it}, \tag{1}$$

where i indicates countries, t indicates year; y_{it} is annual stock trading volume in US dollars, X is the vector of independent variables, including the main explanatory variable of the number of internet users, a proxy of internet usage. Though it is not a direct measure of online usage of investors, it is safe to infer that the more internet users in a country, the more of it.

Elhorst (2003) suggests including the spatial effect into the panel fixed effect model. The spatial correlations can be shown by two different forms: spatial lagged model and spatial error model.

2.2. Spatial lagged model and spatial error model.

$$y = \alpha + \rho Wy + XB + \varepsilon, \tag{2}$$

where W is the spatial weight matrix, n×n, indicating the adjacent conditions between each pair districts. Spatial lagged coefficient ρ indicates potential spatial auto-correlation of Y (annual stock volume). If ρ is significantly different from zero, it indicates the stock volume of country i is correlated with its neighboring markets, which will lead to estimation errors if using traditional OLS models.

If ρ is insignificant, it does not necessarily mean the spatial correlation not existing. The spatial association factor may exist in other variables latent in the error term ε . This model is thus called spatial error model, and illustrated as follows:

$$\begin{cases} y = \alpha + \mathrm{XB} + \varepsilon \\ \varepsilon = \lambda W \varepsilon' + \eta \end{cases}, \tag{3}$$

where λ is the spatial error auto-correlation coefficient, representing that spatial associations are influential through some variables beyond the stock volume itself. The spatial models above are cross-sectional and can extend to spatial panel models.

2.3. Data sources and variable definitions. This study investigates 30 stock markets as listed in Table 1. Their geographic locations were shown in Figure 1

Table 1. Stock index and data sources

Country	Index name	Data source	Country	Index name	Data source
USA	Dow Jones (NY)	SE	Austria	ATX	SE
Canada	S&P TSX Composite	SE	Slovakia	SAX	SE
Mexico	IPC	SE	China	Shenzhen Synthesis	SE
Brazil	Bovespa Index	SE	Hong Kong	Hang Seng	SE
Argentina	Merval Index	SE	Japan	Nikkei225	SE
Germany	DAX PRICE	SE	Korea	Composite Stock Price	SE
France	SBF250	SE	Thailand	SET	SE
UK	FTSE-100	SE	Malaysia	Kuala Lumpur Composite Index	SE
Norway	OBX	Yahoo Finance	Philippines	Manila Composite Index	SE
Sweden	SX ALL SHARE PI	SE	India	BSE 30	SE
Netherlands	AEX	SE	Israel	TA-100	SE
Belgium	BEL 20	SE	Turkey	ISE National 100	SE
Italy	MILAN MIBTEL	SE	Egypt	CMA	SE
Spain	MADRID SE	SE	Australia	ALL ORDS	SE
Hungary	BUX	SE	New Zealand	Wellington	SE

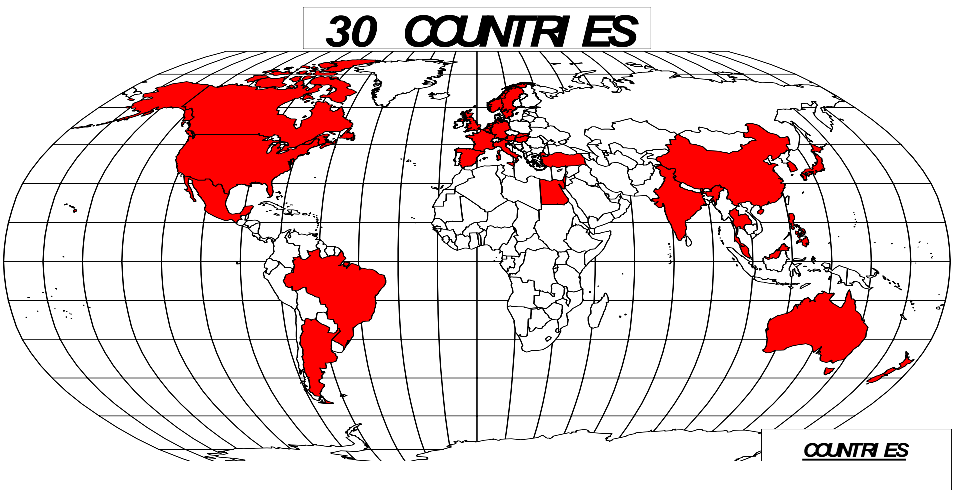

Fig. 1. Geographic location of the 30 countries studied

Except the main variable, the internet usage, we put interpersonal contacts in control in each model, with their potential influences on people's intention to invest (Hong, Kubic and Stein, 2004; 2005), including the variables of people arrival and departure, as well as telephone and mobile phone usage in each country. We believe the more people traveling in and out of a country or more phone usage, the more information exchange among countries. They are positively associated with stock market activities (Portes and Rey, 2005; Hong, Kubic and Stein, 2004, 2005). In sum, variables controlled in empirical models include traditional phone users, mobile phone users, people arrival and people departure. Following is the definitions of each control variable, obtained from the 2006 World Bank WDI database. We expect they show positive signs with stock volumes, based on the findings of Portes and Rey, and Hong, Kubic and Stein.

- Traditional telephone usage (Tel): the number of households using traditional telephone in each country.
- Mobile phone usage ($Mobile$): the user per thousand using mobile phone.
- People arrival ($Arrive$): people arrival for each country every year, scaled by its population.
- People departure ($Depart$): people departure for each country every year, scaled by its population.

In addition, we also control the economic and trade variables in models, due to their substantial roles in stock market. They include per capita GDP ($perGDP$), trade ($Trade$, the sum of import and export of each country divided by its GDP), and net foreign direct investment ($FDII$, FDI inward minus outward). At last, the economy openness/freedom is controlled through the index of economy openness/freedom from the database of Centre D'etudes Prospectives Et D'informations Internationales (CEPII). This index measures the degree of economic openness/freedom of each country by a 1-100 scale. The higher the score is, the more open and free are these countries. We expect positive signs between the economic variables and stock trading. The data sources and operational definitions of each variable are shown in Table 2.

Table 2. Definition of variables

Variable	Variable symbol	Definition/unit
Annual stock volume	$Svolum$	Annual stock trading volume/US dollars
Internet usage	$Internet$	Number of internet users
Traditional telephone usage	Tel	Number of telephone users
Mobile phone usage	$Mobile$	Number of users per thousand people
People arrivals	$Arrive$	Percentage of arrivals over population/%
People departures	$Depart$	Percentage of departures over population/%
Net foreign direct investment	$FDII$	FDI inward minus outward/US dollars
Freedom and openness of economy	$Openness$	Degree of freedom and openness
Per capita GDP	$perGDP$	US dollars
Trade	$Trade$	International trade over GDP/%

3. Empirical results analysis

3.1. Stock volumes and internet usage in 30 markets from 1999 to 2004. Stock trading volumes of each country under study are shown in Table 3. Both the annual average volume and volatility of the 30 countries reached highest in 2000, and lowest in 2003 over the research period.

Table 3. Annual stock market volumes (US $ billion)

	1999	2000	2001	2002	2003	2004	Average	S.D.
Slovakia	4	8	9	7	6	6	7	2
Philippines	198	81	31	31	26	36	68	67
Egypt	90	111	38	25	32	56	59	34
Argentina	77	59	41	13	49	76	53	24
Hungary	143	121	48	59	82	130	98	40
New Zealand	112	107	84	74	104	154	106	28
Austria	116	93	72	58	108	238	115	64
Mexico	360	453	400	277	234	428	359	87
Israel	154	233	297	552	415	462	353	150
Malaysia	485	585	207	276	501	598	442	163
Belgium	591	380	411	338	375	702	466	146
Brazil	872	1012	650	482	604	935	760	210
Thailand	416	232	357	479	973	1,099	593	355
Norway	541	601	523	488	699	1,354	702	328
Turkey	812	1,792	779	706	996	1,474	1,094	440
India	2,788	5,098	2,493	1,971	2,848	3,790	3,165	1,118
Sweden	2,382	3,900	3,015	2,185	2,638	4,124	3,041	805
Hong Kong	2,474	3,778	1,963	2,106	3,316	4,389	3,005	978
Australia	1,943	2,263	2,406	2,946	3,698	5,142	3,067	1,189
Netherlands	4,784	6,772	10,335	4,623	4,634	6,041	6,199	2,209
Korea	8,258	10,680	7,039	7,921	6,827	6,388	7,853	1,550

Table 3 (cont.). Annual stock market volumes (US $ billion)

	1999	2000	2001	2002	2003	2004	Average	S.D.
Canada	3,515	6,347	4,615	4,060	4,678	6,539	4,959	1,226
China	3,771	7,215	4,489	3,333	4,768	7,482	5,177	1,760
Italy	5,364	7,784	5,521	5,398	6,632	8,043	6,457	1,224
Spain	7,443	9,858	8,386	10,140	9,351	11,947	9,521	1,550
France	7,875	10,833	10,773	9,347	9,953	13,117	10,317	1,752
Germany	8,147.40	10,691	14,196	12,331	11,472	14,061	11,816	2,272
Japan	18,492	26,939	18,262	15,733	22,730	34,304	22,743	6,907
UK	13,779	18,353	18,611	19,097	22,115	37,072	21,505	8,081
USA	185,740	318,620	290,410	253,710	155,470	193,550	232,917	64,585
Average	9,391	15,167	13,549	11,959	9,211	12,125	11,901	
S.E.	33,601	57,652	52,573	45,937	28,253	35,448	42,162	

Not to our surprise, the internet usages of each country show consistent rising trend from 1999 to 2004, as Figure 2 demonstrates. There were 82.2 million users in 1999, increased by 191% to 239.5 million users in 2004. The USA is the heaviest user following by China, which has grown very fast.

We examine the cross-sectional relationship between internet usage and stock volume each year, and find they are positively associated, as shown in Figure 3. It seems to support the financial economists' viewpoint that internet activates stock trading. However, it could be spurious correlations and caused by other economic factors. Before jumping into conclusions, we need to check it by multivariate models and put potential factors in control.

3.2. Interpersonal interaction variables. As shown in Table 4, all interpersonal interaction variables show growing trend within the studied period. For instance, in the 30 countries analyzed, there was an average of 237 million households using traditional telephone (Tel) in 1999, growing to 326.7 million in 2004, with annual increase rate 37.8%. For the mobile phone users ($Mobile$), in 1999, there were only 290 users per every 1000 people on average. It increased to 689 in 2004, a 137% increment. The people arrivals and departures in each country ($Arrive$ and $Depart$) also continued to grow within these years. The number of arrivals was higher than that of departures, which might indicate immigration of constant population.

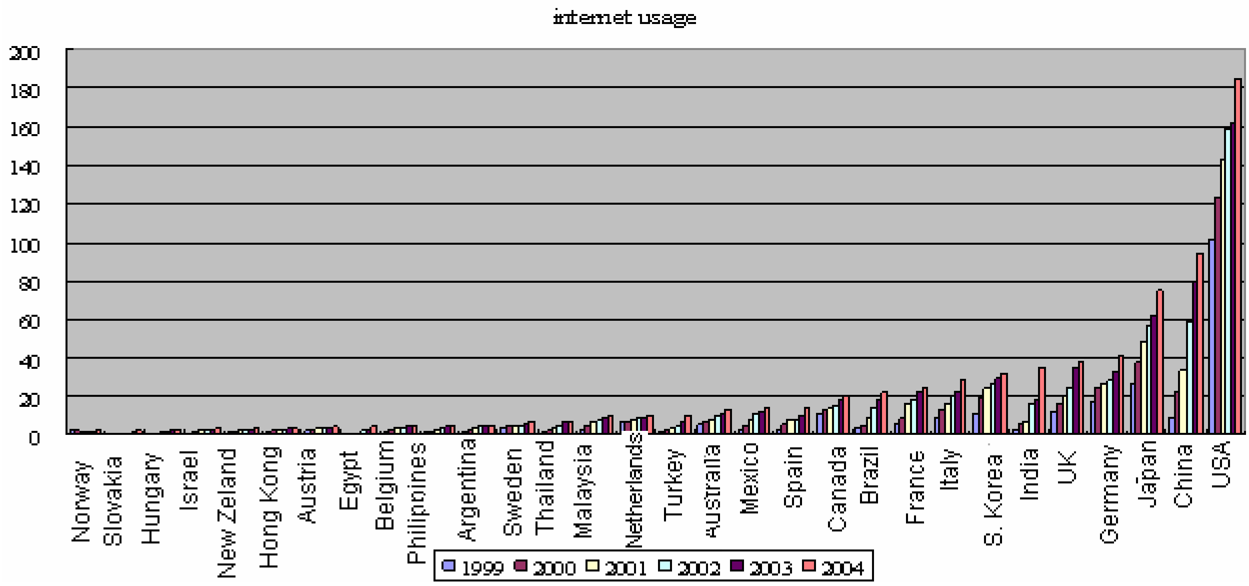

Fig. 2. The internet usage of 30 countries from 1999 to 2004

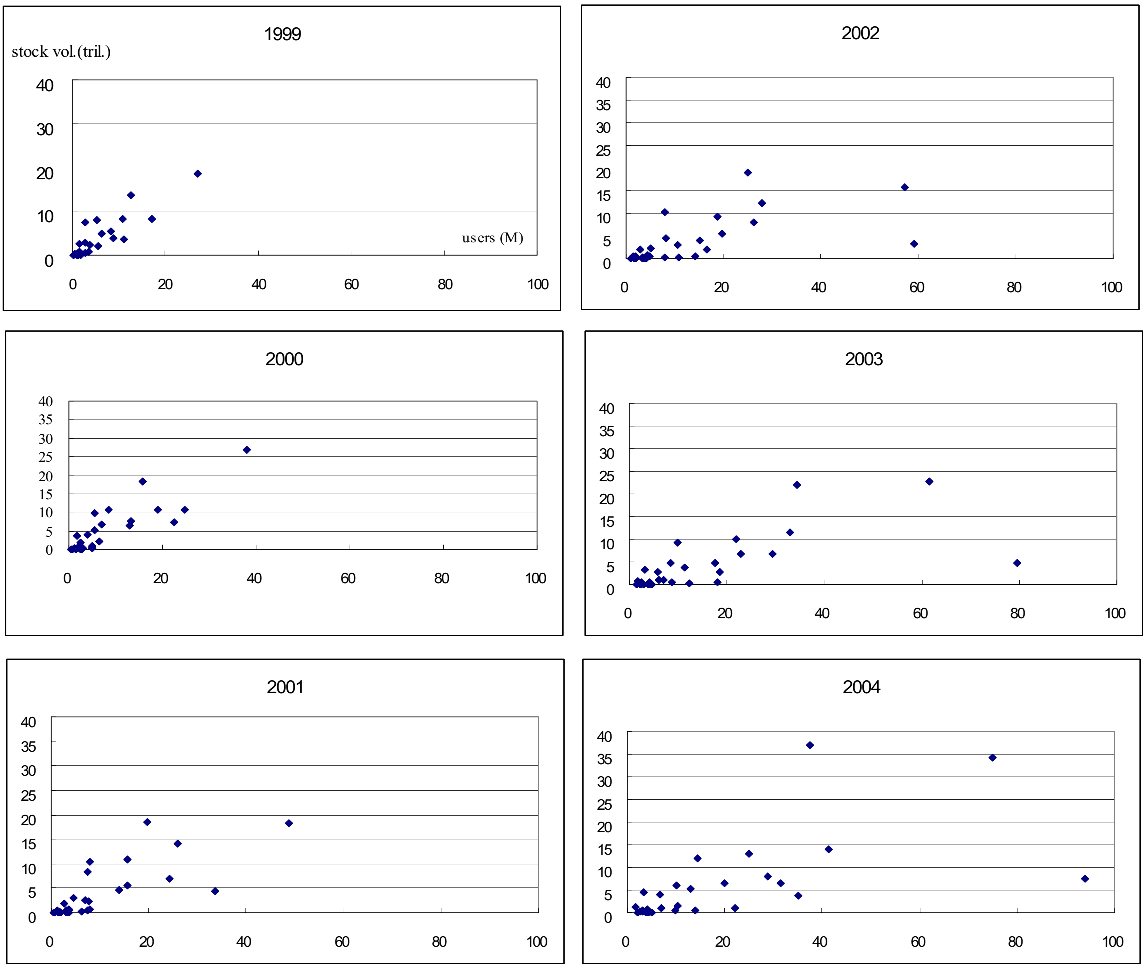

Fig. 3. The relationship between global internet usage and stock volumes: 1999-2004

Note: These exhibits exclude the USA (way out in the right-upper corner) to make the pattern more clear.

3.3. Economic development related variables. Per capita GDP average maintained a stable growth trend from \$17,549 in 1999 to \$18,545 in 2000, and \$21,371 in 2004. The trade over GDP is averagely over 80%. Net inward foreign direct investment reached 449.23 billion in 2000 but dropped drastically to 155.20 billion in 2004. The freedom of economy was quite different among 30 countries. Please refer to Table 5 for details.

Table 4. Descriptive statistics of other information flow variables

Descriptive statistics of the information flow variables from 1999 to 2004, including the households using telephone (Tel, in 10 thousand), mobile phone users per thousand people (Mobile), people arrivals (Arrive) and departures (Depart) over population (in %), net foreign direct investment inflow (FDII, in US \$1 M), openness of economy (openness), etc. Economic openness was scaled from 0 to 100. 30 countries were used as samples in each year.

	Tel	Mobile	Arrive	Depart
1999				
Average	2,370.43	290.99	44.34	38.61
SD	3,766.91	201.32	52.09	37.89
Min	165.54	1.89	0.25	0.41
Max	18,352.00	647.1	218.28	118.54
2000				
Average	2,608.60	413.33	46.93	41.38
SD	4,213.55	262	55.08	39.85
Min	169.8	3.52	0.26	0.43
Max	19,251.00	817.31	224.45	132.77
2001				

Table 4 (cont.). Descriptive statistics of other information flow variables

	Tel	Mobile	Arrive	Depart
Average	2,784.53	502.88	48.33	41.53
SD	4,587.62	286.16	56.58	41.74
Min	155.63	6.23	0.25	0.44
Max	19,170.00	916.29	226.04	154.3
2002				
Average	2,907.55	556.55	50.37	42.29
SD	4,975.35	291.23	61.39	43.06
Min	140.3	12.1	0.23	0.47
Max	21,422.00	964.67	244.08	144.86
2003				
Average	3,061.82	616.6	49.08	43.96
SD	5,567.66	298.21	59.89	44.87
Min	129.47	24.57	0.26	0.5
Max	26,275.00	1,080.30	234.92	141
2004				
Average	3,267.40	689.75	58.03	52.84
SD	6,371.79	301.56	75.04	51.43
Min	125.04	43.81	2.61	4.25
Max	31,244.00	1,184.00	316.9	173.72

Table 5. Descriptive statistics of the control variables of economic development

	Per capita GDP	Trade	FDII	Openness
1999				
Average	17,550	0.78	32,115	67.19
SD	9,607	0.55	57,755	8.92
Min	2,312	0.19	354	48.1
Max	32,854	2.55	289,440	90.4
2000				
Average	18545	0.86	44,924	67.13
SD	10069	0.61	76,016	9.43
Min	2,415	0.2	982	45.7
Max	34,208	2.87	321,270	90.8
2001				
Average	19,125	0.84	22,590	67.34
SD	10,433	0.59	33,644	9.82
Min	2,540	0.2	510	47.1
Max	35,712	2.78	167,020	91.4
2002				
Average	19,640	0.83	16,129	66.38
SD	10,638	0.6	19,739	9.41
Min	2,658	0.21	319	50.5
Max	36,146	2.96	80,840	88.9
2003				
Average	20,232	0.85	13,502	66.13
SD	10,821	0.65	16,851	9.62
Min	2,896	0.22	237	50.9
Max	37,501	3.39	67,091	89.3
2004				
Average	21,372	1	15,520	65.99
SD	11,281	0.73	26,483	9.77
Min	3,139	0.31	-34,903	51
Max	39,676	3.76	106,830	90.1

3.4. Internet effects on stock markets: spatial panel models. According to our empirical results, the internet usage has a significantly negative effect on stock trading in all models, including the basic panel regression model and spatial panel models. It indicates that the internet usage has been hindering, instead of fostering, the global stock market trading[1]. In compliance with the argument of Sociology, the results suggest that the overflow of internet information turns people into information anxiety and inactivates trading of stock investors as a whole. The only significant variable other than internet for all models is per capita GDP, with positive signs. It represents that economic factors play the fundamental role in stock market trading. All interpersonal interaction variables show negative signs, though none is significant. It probably proposes that economic development is the real major factor, and thus the marginal effects of interpersonal interaction turn out to be insignificant.

As for the spatial correlation, the R-square is very low, only 1.68% in the basic panel model without considering spatial factor (see first column of Table 6). However, in the spatial panel models, the R-squares drastically rise to 0.98. It represents that the spatial correlation plays an influential or dominant role in global stock trading. The spatial correlation is not shown directly in the dependent variable of stock trading, because the coefficient of spatial lagged item ρ is not significantly different from zero. Rather, the spatial correlation is demonstrated through the error term. The value of λ is 0.24, with p-value being 0.013. In a word, the empirical results signify the importance of spatial correlation to global stock market trading; stock market trading is greatly inter-correlated among neighboring markets.

Table 6. Internet effects on global stock market trading

Dependent variable is each country's stock trading volume from 1999 to 2004. *Tel*, *Mobile*, *Arrive*, *Depart*, respectively, represent the households using traditional telephone, mobile phone users, people arrival and departure. *FDII*, *perGDP*, *Trade*, and *Openness* were another set of control variables. They respectively represent foreign direct investment net inflow, per capita GDP, trade over GDP, and openness and freedom of the economy. All the variables were analyzed by log, except for *Trade* and *Openness*.

Model	Panel model		Spatial lagged model: country-specific fixed effect		Spatial error model: country-specific fixed effect	
Explainable variables	Coeff.	P value	Coeff.	P value	Coeff.	P value
Constant	2.32	0.5850				
Tel_{it}	-0.32	0.3610	-0.02	0.4947	-0.02	0.4724
$Mobile_{it}$	-0.02	0.7740	-0.04	0.5052	-0.04	0.4554
$Internet_{it}$	-0.34***	0.0090	-0.37***	0.0002	-0.38***	0.0003
$Arrive_{it}$	-0.36	0.0800	-0.10	0.1493	-0.09	0.1770
$Depart_{it}$	0.13	0.6980	-0.04	0.3321	-0.03	0.5251
$FDII_{it}$	0.15***	0.0020	0.01	0.1759	0.01	0.1524
$perGDP_{it}$	2.89***	0.0020	3.13***	0.0000	3.13***	0.0000
$Trade_{it}$	0.19	0.1880	0.06	0.5351	0.08	0.4243
$Openness_{it}$	0.00	0.8100	0.00	0.7164	0.00	0.6896
Self spatial correlation coefficient			0.08	0.4209		
Error spatial correlation coefficient					0.24**	0.0136
F(P value)	3.89(0.0002)					
R-square	0.0168		0.98		0.98	
Rbar-squared			0.98		0.98	
sigma^2			0.0184		0.0180	
log-likelihood			103.87		104.81	
Number of samples			180		180	

Note: *** statistically significant at 1%, ** statistically significant at 5%

[1] We attempted to add the stock return as another independent variable. The coefficient is insignificant. Hence, the models reported here do not show it.

Conclusion

How is the global stock market affected by the rapid increase in Internet usage? With the online information flow being vast and quick, the literature shows that investors trade more and more frequently. Yet, it also shows that when information overflows, many internet users become anxious and shy away from decision making. We examine the internet effects on stock trading in 30 markets by building spatial panel models. Although we are subject to the limitations of the measurement error of internet usage, we believe the findings are valuable in understanding the internet usage impacts on global impacts. Empirical results demonstrate negative internet effects on stock trading. The internet usage hinders, rather than facilitates, the stock trading. We ponder upon this and propose that there could be a threshold in the internet usage. When it grows up in the beginning, it activates investors to trade, but turns into holding back their trading when it increases over a threshold and puts investors under overwhelm.

Moreover, empirical results demonstrate significant spatial error auto-correlation. Without considering it, the basic panel model's explanation power is very low, only 1.68%. In the spatial panel models, it increases to 98%. The global stock trading is highly special inter-correlated; spatial econometric models are more appropriate than OLS models. With the rapid development and growth of internet social media, we need more research to explore the impacts of social network on web. The social network analysis might be a good vehicle for financial scholars to borrow and apply.

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Appendix A. The spatial regression models

1. Panel regression model

To examine the internet effect, the basic panel regression model is as follows:

$$y_{it} = \alpha_i + \beta\, e_{it} + Z_{it}\Gamma + \varepsilon_{it}\,, \tag{1}$$

where α_i is constant; i indicates countries i=1,……, 30. N=30; t indicates time t=1999, ……, 2004. T=6; y_{it} is annual stock trading volume in US dollars; e_{it} is the number of internet users, a proxy of internet usage. Though it is not a direct measure of online usage of investors, it is safe to infer that the more internet users in a country, the more of it. Z_{it} is control variable vector, including the information flow variables other than internet, and economic development variables. We will discuss it in the following section. ε_{it} is error vector, $\varepsilon_{it} \sim N(0,\sigma^2 I)$.

If the hypothesis of random effect is refused in the panel regression model, and country-specific fixed effect fits better, the potential spatial correlation may cause errors in estimating the model (Giuseppe and Gianfranco, 2005). Elhorst (2003) suggests including the spatial effect into the panel fixed effect model. The spatial correlations can be shown by two different forms: spatial lagged model and spatial error model. For the former, it adds a spatial-lag dependent variable as an independent variable; for the spatial error model, it adds another spatial error autocorrelation equation in the model; unconditional likelihood function is adopted to estimate parameters. The next section will introduce these models in more detail.

Appendix B. Spatial lagged model and spatial error model

Anselin (1998, 1999) developed the spatial auto-regression model, or spatial lagged model, as equation (2):

$$y = \alpha + \rho Wy + X\beta + \varepsilon\,, \tag{2}$$

where ρ is spatial auto-regression coefficient; ε is error vector, $\varepsilon \sim N(0,\sigma^2 I)$; W is spatial weight matrix, n×n, to demonstrate the adjacent conditions between each pair districts. If districts i and j are adjacent, w_{ij} = 1; if i and j are non-adjacent or if $i = j$, w_{ij} = 0. As illustrated below:

$$W_{ij} = \begin{pmatrix} 0 & w_{12} & \Lambda & w_{1n} \\ w_{21} & O & & M \\ M & & O & M \\ w_{n1} & \Lambda & \Lambda & 0 \end{pmatrix}$$

Spatial lagged coefficient ρ indicates potential spatial auto-correlation of Y (annual stock volume). If ρ is significantly different from zero, it indicates the stock volume of country i is correlated with its neighboring markets, which will lead to estimation errors if using traditional OLS models. Due to its similarity with the lagged item in auto-regression time series models, it is thus called spatial lagged model.

The adjacency is defined according to data forms: regional, point-referenced or grid data (Anlesin, 1998; Pace, Barry and Sirmans, 1998; Bivand, 1998). The 30 countries studied in this paper fit grid data, since they cover only part, instead of all, countries in the world. The adjacency in grid data has three different definitions: Rook's, Bishop's and Queen's. Rook's definition represents the areas in the above, below, left and right of the target area are defined adjacent; Bishop's means the areas in the four corners of the target area are defined adjacent. We adopt Queen's definition – the combination of Rook's and Bishop's ones. That is, all the areas around the target are defined adjacent, as the grey areas in Figure 1. And the grid data of 30 markets in this study are shown in Figure 2.

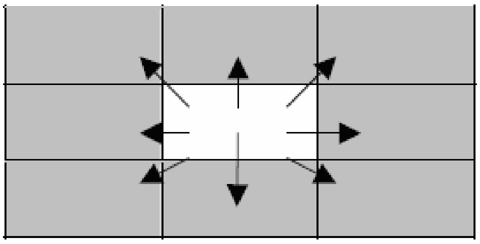

Fig. 1. Queen's definition of adjacency in grid data

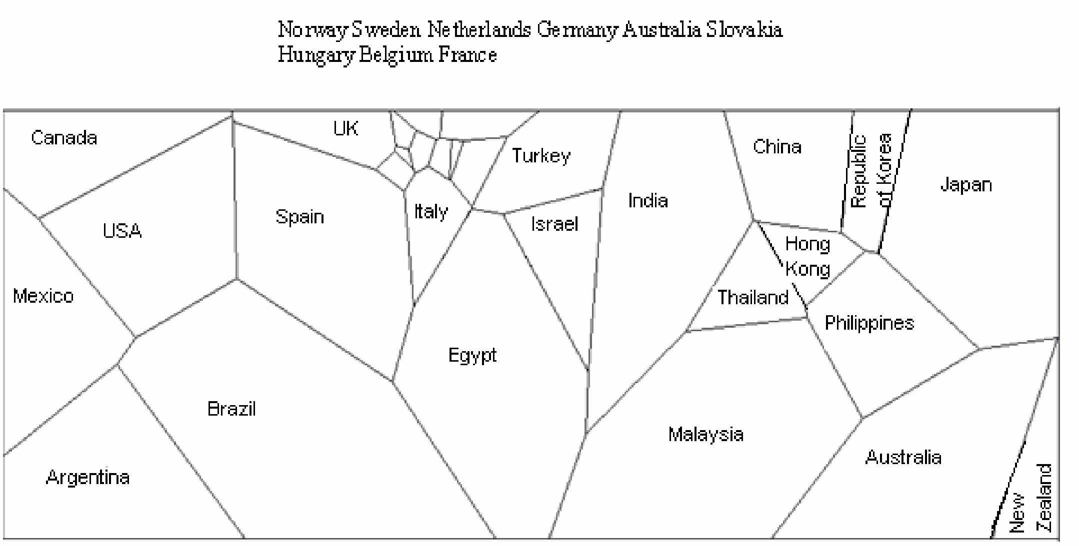

Fig. 2. The grid map of 30 stock markets covered in this study

If ρ is insignificant, it does not necessarily mean the spatial correlation not existing. The spatial association factor may influence other variables which are latent in the error term ε . This model is thus called spatial error model, illustrated as follows:

$$\begin{cases} y = \alpha + \mathrm{XB} + \varepsilon \\ \varepsilon = \lambda W \varepsilon' + \eta \end{cases}, \tag{3}$$

where λ is the spatial error auto-correlation coefficient, representing that spatial associations exist through some latent variables, instead of stock volume itself. And η_{it} is the error vector, $\eta_{it} \sim iid\, \mathrm{N}(0, \sigma^2)$.

The spatial models above are cross-sectional and can extend into spatial panel models, introduced as follows.

Appendix C. Spatial panel models

(1) Spatial lagged panel model

The panel fixed effect could be country-specific (μ_i) or year-specific (θ_t). The former is shown through dummy variables indicating countries; the latter through dummies indicating years. Accommodating the fixed effect of panel model into a spatial lagged model or spatial error model, we get the spatial lagged panel model (as illustrated in model (3)) and the spatial error panel model (shown as model (4)):

$$y_{it} = \rho W y_{it} + \beta\, e_{it} + \mathrm{Z}_{it}\Gamma + \mu_i + \theta_t + \varepsilon_{it} \tag{4}$$

and

$$\begin{cases} y_{it} = \beta\, e_{it} + \mathrm{Z}_{it}\Gamma + \mu_i + \theta_t + \varepsilon_{it} \\ \varepsilon_{it} = \lambda W \varepsilon'_{it} + \eta_{it} \end{cases}, \tag{5}$$

where

μ_i is the dummy variable of the *i*-th country. Its coefficient represents the specific country effect. θ_t is the dummy variable of the *t*-th year. Its coefficient represents the specific year effect. ε_{it} is error vector, $\varepsilon_{it} \sim N(0, \sigma^2 I)$, η_{it} is error vector, $\eta_{it} \sim iid\, \mathrm{N}(0, \sigma^2)$.