An Intelligent Web-based GRA/Cointegration analysis for Systematic Risk

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Abstract**—**A new intelligent web-based grey relational analysis (GRA)/cointegration analysis is proposed to examine the effects of cross-border bank M&As on the systematic risk that took place in the American, Asia, Europe, Africa and Middle East of banks in this paper. The potential diversification gains that arise from geographic or cross-border diversification are studied using a database that includes deals and bank stock return information for 114 cross-border M&As during 1998-2005. Cointegration analysis is first developed to obtain the relationship between financial variables and web-based GRA is then applied to establish the ranking and clustering of all acquirer events. The findings have important regulatory policy implications in that, the potential diversification gains have obtained in home country. Consequently, regulators in home countries may be less concerned with a rise in systematic risk following cross-border M&As, and no need to impose barriers to restrict the cross-border M&As activity. Grey relational analysis is demonstrated to be well developed to the clustering and ranking of cross-border M&As events. This study suggests that the proposed intelligent web-based GRA/cointegration analysis is effective and robust.

Keywords**—**cross-border Mergers and Acquisitions (M&As), cointegration, grey relational analysis (GRA), systematic risk.

I. Introduction

THE international financial market has experienced significant changes that have reshaped its exposure to global shocks. An important issue I this trend has been the increasing presence of foreign banks in emerging markets and developed countries.

The worldwide integration, derive from cross-border M&As in bank have been on the rise for over a decade. Focarelli and Pozzolo [1] suggest that distance, economic and cultural integration are important determinants for both the banks' and the insurance companies' expansion abroad. By extending its operations into new overseas markets, the acquirer bank is confronted with potentially new and risk increasing monitoring problems of the target bank, such as loan customer base, the operating cost structure, etc. DeYoung et al [2] point out the evidences on the impact of both geographic and product diversification via merger is mixed. A limited number of recent studies have examined systemic risk issues in European banking, and none of them directly examined the impact of bank M&A. Prior literatures examine the performance effects to b bank acquisitions [3]-[5]. The effects of bank M&As have been studied by using information from M&As between local institutions in developed countries and cross-border M&As in Europe [6],[7]. Micco et al. [8] show limited performance improvements in the post-acquisition period. On the contrary, foreign banks in emerging markets are found to be better performers than their domestic counterparts. On the other hand, a common argument in banking literatures is that cross-border M&As have the potential to reduce bank's insolvency risk [9]-[12]. Amihud et al. [13] propose that cross-border mergers may increase the insolvency risk exposure of either one or both the acquirer and target bank regulators. Instead, Nicoló, et al. [14] find highly concentrated banking systems exhibited levels of systematic risk potential higher then less concentrated systems during the 1993-2000 period, and argue that bank consolidation and conglomeration may not necessarily yield either safer financial firms or more resilient banking systems.

A first set of studies analyzes the effects of cross-border M&As. The strand of the literatures focus on the effect of M&As on stock prices and accounting measures of performance. Piloff and Santomero [15] and Calomiris and Karceski [16] review the findings for U.S. institutions. The typical analysis of M&As using stock price data, compares the change in returns after a M&A is announced. Another strand of studies uses accounting data to assess the effect of M&As on operating performance. Chamberlain [17] analyzes a sample of M&As that took place in the U.S. in the 1980s and finds that these transactions did not yield any operating efficiencies. This result is consistent with similar evidence by Linder and Crane DB [18] that shows no improvements in Return on Assets (ROA) or growth in operating income in the same period. The study expands these last two strands of the literature by using accounting data of publicity bank M&As to assess the effect of cross-border acquisitions on the acquirers' systematic risk. The grey relational analysis (GRA) has been used in predicting of linear motion guide [19],[20]. In the financial research, a hybrid model combining grey prediction and rough set approach that predicts the failure firms based on past financial performance data [21], and applying grey group model to forecast the earning per share [22]. The results demonstrate that the grey model is a competitive and competent one in prospective analysis. To analyze the M&As effect, this study develop a new intelligent GRA/cointegration analysis for systematic risk and constructs a large sample of M&As that includes acquirers in developed and emerging markets.

II. Hypothesis and Methodology

A. Hypothesis and Empirical Model

The study analyzes the changes in the acquiring bank's systematic risk after the cross-border M&As is completed compared to its risk prior to the M&As, relative to an index of all banks in three domiciles: the world, the home country (i.e., the country where the acquiring bank is located) and the host country (i.e., the country where the target bank is located).

In accordance with Amihud et al. [13] argument that after a domestic bank (acquirer) acquires a foreign bank (target), there is a rise in the share of its income that is derived from foreign markets (host country) and a decline in the share of its income that is derived from the domestic market (home country). This study examines the issue and proposes the hypothesis as follows:

H_1^1 : Since part of the acquirers' return is generated by banking operation abroad (or target) which is not perfectly correlated with banking activity in the home market, as a result, as would be expected from the diversification theory, the acquiring bank's systematic risk (λ_{home})should decline after cross-border M&As.

H_1^2 : Since the acquirers' return in part reflects the return on banks in countries where the target bank is doing banking activity, which is generated by banking operation abroad (or target) that is correlated with banking operation in the home market, as a result, λ_{world} and λ_{host} should increase after cross-border M&As.

The study expects that a cross-border M&As would decrease the acquirers' β with respect to the home bank return and increase its β with respect to the world and host bank return.

Specifically, this study measures the acquiring banks' systematic risk, its β coefficient, relative to three bank indexes: world, home and host. To attain this objective, the study uses the bank return of world, home and host respective, RB_{world} , RB_{home} and RB_{host} . This is obtained by regressing the world, home and host bank return indexes on the individual acquirers' return, respectively. The estimated model for cross-border and domestic M&As of the return of stock i on day t, $R_{i,t}$, are as follows:

$$\begin{aligned} \mathrm{R}_{i,t} &= \alpha_i + \beta_{world,i}\mathrm{RB}_{world,t} + \lambda_{world,i}\mathrm{RB}_{world,t}\mathrm{D}_t \\ &+ \beta_{home,i}\mathrm{RB}_{home,t} + \lambda_{home,i}\mathrm{RB}_{home,t}\mathrm{D}_t + \beta_{host,i}\mathrm{RB}_{host,t} \\ &+ \lambda_{host,i}\mathrm{RB}_{host,t}\mathrm{D}_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

$$\begin{aligned} \mathrm{R}_{i,t} &= \alpha_i + \beta_{world,i}\mathrm{RM}_{world,t} + \lambda_{world,i}\mathrm{RM}_{world,t}\mathrm{D}_t \\ &+ \beta_{home,i}\mathrm{RM}_{home,t} + \lambda_{home,i}\mathrm{RM}_{home,t}\mathrm{D}_t \\ &+ \beta_{host,i}\mathrm{RM}_{host,t} + \lambda_{host,i}\mathrm{RM}_{host,t}\mathrm{D}_t + \theta_{i,t} \end{aligned} \tag{2}$$

$$\begin{aligned} \mathrm{RB}_{i,t} &= \alpha_i + \beta_{world,i}\mathrm{RM}_{world,t} + \lambda_{world,i}\mathrm{RM}_{world,t}\mathrm{D}_t \\ &+ \beta_{home,i}\mathrm{RM}_{home,t} + \lambda_{home,i}\mathrm{RM}_{home,t}\mathrm{D}_t \\ &+ \beta_{host,i}\mathrm{RM}_{host,t} + \lambda_{host,i}\mathrm{RM}_{host,t}\mathrm{D}_t + \varphi_{i,t} \end{aligned} \tag{3}$$

Where $R_{i,t}$ is the return on acquirer i on day t, $RB_{K,t}$ is the bank index on day t, where K = world, home or host, and D_t is a dummy variable, $D_t = 0$ for days -365 to day -1 before the M&As announcement, and $D_t = 1$ for days +1 to day +365 after the consummation of the M&As. We can directly obtain the change in beta from (4): $\Delta\beta_{K,i} = \lambda_{Ki}$.

$$\Delta\beta_{K,i} = \beta_{K,i}(after) - \beta_{K,i}(before) = \lambda_{K,i} \tag{4}$$

B. Definition of web-based grey relational analysis (GRA)

To establish the prediction model based on grey relational analysis (GRA), the definition of GRA model is introduced by following the concepts presented by [23],[24]. The definition of grey relational analysis (GRA) is first presented as follows.

A system which has none of information is defined as a black system, while a system which is full of information is called white. Thus, when the information of a system is either incomplete or undetermined, it is defined as grey system. The grey number in grey system represents a number with less complete information. The grey element represents an element with incomplete information. The grey relation is the relation with incomplete information. This section describes the basic definitions of grey relational analysis, GRA. The inner product and metric of two vectors are first defined. What follows are properties of norm space, grey relational space, grey relational grade for both globalized and localized grey relationships.

Definition1. Let the set X be a vector space to apply grey relational analysis, and the vectors x, y are elements of X . First, the inner product of x and y and metric of vectors is defined as follows:

$$\langle x, y \rangle = \|x\|_\xi, \|y\|_\xi \cos\theta \tag{5}$$

$$\text{Where } x, y \in R^n \text{ , } x = (x_1, x_2, \ldots.., x_n)^T \tag{6}$$

$$\|x\|_\xi = \sqrt[\xi]{\sum_{i=1}^{n} x_i^\xi} \tag{7}$$

The X is content with the vector space axiom. Eq. (5) is satisfied with the inner product axiom. Both axioms are in set theory [24].

Definition 2. The metric between two vectors x, y with the distinguish coefficient ξ is defined as follows:

$$\|x-y\|_{\xi} = \sqrt[\xi]{\sum_{i=1}^{n} |x_i - y_i|^{\xi}} \tag{8}$$

Where $\xi \geq 1$.

Eq. (8) defines Minkowski distance [25]. The Euclidean distance is the special case of Eq. (8) at $\xi = 2$, and city-block distance is also the special case of Eq. (8) at $\xi = 1$.

Axiom 1. The X is a norm space, as consisted with the following three properties.

1. $\|x\|_{\xi} \geq 0$
2. $\|\alpha x\|_{\xi} = |\alpha| \cdot \|x\|_{\xi}$,

Where $\alpha \in R$

3. $\|x+y\|_{\xi} \leq \|x\|_{\xi} + \|y\|_{\xi}$

The third property in L_P norm has been proved mathematically.

Definition 3. The following two features that are able to extract from traditional GRA concept are describe as follows:

1. The metric between two sequences is calculated, and normalized the grey relational grade with distinguish coefficient.
2. Grey relational grade has the order relation of each sequence.

Definition 4. The Γ is a grey relational space, such as $\Gamma \subset X \times X$. The current GRA is a process that transfers Banach space into the grey relational space, and is content with Def. 3. The former is described by

$$f : X \to \Gamma \tag{9}$$

Definition 5. The variables x_0 and x_i are both n-dimensional vectors, such as $x_0, x_i \in X$, which is the replaced sequence in GRA. Note that x_0 is a reference vector, and x_i is an inspected vector, where $i = 1,2,.....m$.

Definition 6. The grey relational grade γ_{ij} is defined as a value obtained by grey relational analysis, which is given for the ordered pair $(X_i, X_j) \subset \Gamma$.

Definition 7. The localized grey relational grade γ_{0i} can be defined as follows:

$$\gamma_{0i} = \frac{\Delta_{\max} - \Delta_{0i}}{\Delta_{\max} - \Delta_{\min}} \tag{10}$$

Where

$$\Delta_{0i} = \|x_0 - x_i\|_{\xi}$$

$$\Delta_{\max} = \max_{\forall i} \{\Delta_{0i}\}$$

$$\Delta_{\min} = \min_{\forall i} \{\Delta_{0i}\}$$

Theorem 1. The globalized grey relational grade γ_{ij} can be represented as follows:

$$\gamma_{ij} = 1 - \frac{\Delta_{ij}}{\Delta_{\max}} \tag{11}$$

Where $i, j = 1,2,....m$,

$$\Delta_{ij} = \|x_i - x_j\|_{\xi}$$

$$\Delta_{\max} = \max_{\forall i} \max_{\forall j} \{\Delta_{ij}\}.$$

Eq. (11) is equivalent to Eq. (10), such as

$$\gamma_{ij} = \frac{\Delta_{\max} - \Delta_{ij}}{\Delta_{\max} - \Delta_{\min}} \tag{12}$$

In Eq. In Eq. (12), $\Delta_{\min} = \Delta_{ii} = 0$ because Δ_{ii} becomes a oneself metric at $i = j$. Hence, Eq. (12) is described as follows:

$$\gamma_{ij} = \frac{\Delta_{\max} - \Delta_{ij}}{\Delta_{\max}} = 1 - \frac{\Delta_{ij}}{\Delta_{\max}}$$

Definition 8. In the current GRA model, the grey relational matrix Γ is defined as follows.

$$\Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1m} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{m1} & \gamma_{m2} & \cdots & \gamma_{mm} \end{bmatrix} \tag{13}$$

The current GRA have the following properties, and several differences from traditional GRA can be found in [26].

Theorem 2. Localized grey relational grade has the following three properties:

Normality: $0 \leq \gamma_{0i} \leq 1 (\gamma_{oi} \in [0,1])$

Isolation:

$\|x_0 - x_i\|_{\xi} = \Delta_{\max} \Leftrightarrow \gamma_{0i} = 0$

Closeness:

$\|x_0 - x_i\|_{\xi} = \Delta_{\min} \Leftrightarrow \gamma_{0i} = 1$.

Theorem 3. Globalized grey relational grade also has the following four properties:

1. *Normality:* $0 \leq \gamma_{ij} \leq 1 (\gamma_{ij} \in [0,1])$
2. *Isolation:* $\|x_i - x_j\|_{\xi} = \Delta_{\max} \Leftrightarrow \gamma_{ij} = 0$
3. *Coincidence:*
   i) $\gamma_{ii} = 1$

ii) $x_i = x_j \Leftrightarrow \gamma_{ij} = 1$

4. Symmetry: $\gamma_{ij} = \gamma_{ji}$.

Theorem 4. Both localized and globalized grey relational grades have three properties, which are similar to the traditional GRA [27], as follows:

Reflexive law: $x_i < x_i$

Anti-symmetrical law:

$x_i < x_j, x_j < x_i \Rightarrow x_i = x_j$

Transitive law:

$x_i < x_j, x_j < x_k \Rightarrow x_i < x_k$

Where $i \neq j \neq k$.

Theorem 5. Grey relational matrix Γ is a symmetric matrix, and every diagonal element turns out to be $\gamma_{ii} = 1$.

III. Data and Statistics Summary

For the analysis of systematic risk, the study compares the magnitude of acquirer's risk one year after the M&As with its risk one year prior to the M&As announcement. Specifically, this study analyzes data from +1 to +365) days after an M&As is completed and compare the results with data –1 to -365) days before an M&As is announced. This study measures the changes in systematic risk using bank return and market return indexes as benchmarks. The event window is the 731-date period surrounding the announcement of the M&As, from 365 days before the M&As announcement to 365 day after it was announced (days -365 to +365). Cybo-Ottone and Murgia [6] find significant leakage effects for cross-border mergers in the days just prior to announcements of European bank mergers. Consequently, the event window of 731 days captures possible leakages of information before the merger is announced. We amalgamate the cointegration model with intelligent GRA approach to provide a more robust and effective solution for the current analysis. The forecasted results are then explored by using (1-3). We examine M&As where at least one partner is financial industry and the partners are headquartered in different countries for cross-border M&As. We use those M&As where the acquirer owns at least 51%~100% of the target after the M&As, and the M&As must be completed by December 2005. The following section presents the empirical results.

Table 1 shows the national and geographical identities of acquirers and targets for cross-border M&As. The United States (9 acquirers) and United Kingdom (18 targets) accounted for the majority of M&As transactions in the sample followed by Thailand and Spain. The sample varied significantly by region within the banking industry. Almost half of the sample (60 acquirers and 77 targets) included bank within the European Union, followed by Asia (35 acquirers and 20 targets). Furthermore, the transactions of M&As reach their peak at 2005 (21 cross-border M&As). The evidence is less supportive of the view that cross-border M&As are more frequent between similar countries, the phenomena is the same as Focarelli and Pozzolo [1].

Table 2 shows the statistics summary of acquirer banks' daily return, bank return and market return relative to three indexes: world, home, and host, respectively. The study finds that the mean value of targets' stock returns for cross-border M&As are both higher than the bank return and market return relative to three indexes: world, home and host. The evidences imply that the targets' stock returns for cross-border M&As increases relative to market return of banks in the acquirers' home country. Alternatively Table 2 presents the results of total risk increasing hypothesis is supported by the standard deviation of a target's stock return. There is a significantly indication of a highest in the targets' total risk relative to its home bank indexes as well as market indexes for cross-border M&As. The result implies that, after the M&As, the operations of the acquirer and target became more integrated, which in turn is likely to have increased the correlation between their return and thus increased their total risk, compared to risk prior to M&As. Overall, the evidence is that in cross-border M&As, the acquirers' total risk does not rise relative to the host country. Thus, the results show that while the target's total risk does not decline after cross-border M&As, as would be expected from the diversification theory, it does riskier relative to target bank. The above evidences imply that in general, cross-border M&As do not lead acquirers to engage in post-merger risk shifting or risk increasing behavior. This result has important regulatory implications. Bank regulators that are concerned with the total risk of their domestic banking institutions need not be overly concerned that cross-border M&As strategies cause a threat to domestic bank industry stability. Consequently, regulators in acquirer's countries may be less concerned about imposing barriers to foreign direct investment.

IV. Empirical Results

In Table 3, the results of coefficients of (1), (2) and (3) for all events are listed. All negative numbers are listed in parentheses. To provide further evidences, these coefficients are summarized in Table 4 according to the sign of each value. This study expects most cases to fall into the expectation where $\lambda_{\mathrm{hom}e,i} < 0$, $\lambda_{world,i} > 0$ and $\lambda_{host,i} > 0$ for cross-border M&As. The results of (1) show that 50.88% (58 M&As deals) of cross-border M&As sample adheres to this expectation, wherein 38.60% (44 M&As deals) are negative significantly at 5% for the changes in beta using bank return indexes as benchmarks. The result further confirms that cross-border bank related M&As do shift the acquirers' systematic risk away from the home market, nevertheless not significantly, as might be expected a priori, and in accordance with the evidence of Agmon and Lessard [28]. On the other hand, the results show that 50.88% (58 M&As deals) of cross-border M&As sample adheres to this expectation, in which $\lambda_{world,i}$ and $\lambda_{host,i}$ are positively, wherein 44.74% (51 M&As deals) and 38.60% (44 M&As deals) are positive significantly at 5% for the changes in beta using bank return indexes as benchmarks, respectively. These results have important regulatory implications. There is a decrease in systematic risk with respect to the bank return index of the home country, where the acquirer is located. Thus regulators in home countries may be less concerned about imposing barriers to cross-border M&As. Furthermore, the changes of systematic risk are both increases significantly with respect to the bank return index of the world and host country, where the target is located. Thus, regulators in host countries may be more concerned regarding the effects of cross-border bank M&As on the stability of their banking systems, to impose barriers to foreign acquisitions.

Furthermore, in Table 4, the evidences are less supportive of the expectation where $\lambda_{\mathrm{hom}e,i} < 0$, $\lambda_{world,i} > 0$ and $\lambda_{host,i} > 0$ for cross-border M&As. The results in (2) show that 45.61% (52 M&As deals) of cross-border M&As sample adheres to this expectation, wherein 39.47% (45 M&As deals) are negative significantly at 5% for the changes in beta using market return indexes as benchmarks. The result further confirms that cross-border bank related M&As do shift the acquirers' systematic risk away from the home market, nevertheless not significantly, as might be expected a priori, and in accordance with the evidence of Agmon and Lessard [28]. On the other hand, the results, presented in Table 4, show that 39.47% (45 M&As deals) and 49.12% (56 M&As deals) of cross-border M&As sample adheres to this expectation, in which $\lambda_{world,i}$ and $\lambda_{host,i}$ are positively, wherein 35.09% (40 M&As deals) and 33.33% (38 M&As deals) are positive significantly at 5% for the changes in beta using market return indexes as benchmarks, respectively.

The result of acquirers' bank return, presented in (3) of Table 4, shows that 42.98% (49 M&As deals) of cross-border M&As sample adheres to this expectation, wherein 39.47% (45 M&As deals) are negative significantly at 5% for the changes in beta using market return indexes as benchmarks. The result further confirms that cross-border bank related M&As do shift the acquirers' systematic risk away from the home market, nevertheless not significantly, as might be expected a priori, and in accordance with the evidence of Agmon and Lessard [28]. On the other hand, the results, presented in Table 4, show that 42.98% (49 M&As deals) and 49.12% (56 M&As deals) of cross-border M&As sample adheres to this expectation, in which $\lambda_{world,i}$ and $\lambda_{host,i}$ are positively, wherein 40.35% (46 M&As deals) and 35.09% (40 M&As deals) are positive significantly at 5% for the changes in beta using market return indexes as benchmarks, respectively.

Finally, grey relational analysis is conducted using the coefficients in Table 3 as source data. All $\lambda_{\mathrm{hom}e,i}$, $\lambda_{world,i}$ and $\lambda_{host,i}$ obtained from (1) to (3) are applied to generate grey relationship. The optimum benchmark value of $\lambda_{\mathrm{hom}e,i}$ for GRA model is the event that have minimum value, while those for $\lambda_{world,i}$ and $\lambda_{host,i}$ are the corresponding maximum values. The results are obtained and listed in Table 4. There are four GRA clustering models in this table, depending on which equation's coefficients are used. The first column shows the GRA ranking of all events, in which the first place represents better and positive effects of decreasing systematic risk while the last position means the positive effects of decreasing systematic risk is not obvious. The next pairs of columns show the results based on coefficients of (1), (2), (3) and all the three equations, respectively. Each pair of column lists the ranking of event number as well as the Gamma values of GRA analysis. The event having higher value of Gamma represents that it has closer grey relationship with the optimum benchmark. All events are clustered into three major groups according to the distribution of grey relationships, which are shown in Fig. 1-4. In table 4, the first and the third groups are shadowed. The first group represents for the best diversification effect after cross-border M&As. These international financial banks are suggested to be the better targets for investment.

The results have important regulatory implications. There is a decrease in systematic risk with respect to the market return index of the home country, where the acquirer is located, as in accordance with the evidence of Agmon and Lessard [28]. Additionally, the changes of systematic risk are both increases significantly in systematic risk with respect to the market return index of the world and host country, where the target is located. Thus, there is further confirming that regulators in home countries may be less concerned about imposing barriers to cross-border M&As. In addition, regulators in host countries may be more concerned regarding the effects of cross-border bank M&As on the stability of their banking systems, to impose barriers to foreign acquisitions.

V. Conclusion

We proposed a new intelligent web-based GRA/cointegration analysis for systematic risk and construct a large sample of M&As that includes acquirers in developed and emerging markets. This study uses a database that includes deals and bank stock return information for 114 cross-borders M&As between 1998-2005, to examine the effects of cross-border bank M&As on the systematic risk of acquiring banks, and to analysis the potential diversification gains that arise from geographic or cross-border diversification. We find that whether an acquirer systematic risk rises or falls, following a cross-border M&As, is highly distinguishing. These results show that both H_1 and H_2 hypothesis are supported by the data of cross-border M&As in general for the changes in beta using bank return and market return indexes as benchmarks. Grey relational analysis was proved to be an effective tool for the clustering and ranking of cross-border M&As events. The first group which has higher value of Gamma by web-based GRA analysis represents for the best diversification effect after cross-border M&As. These international financial banks are suggested to be the better targets for investment. Surprisingly, the effect of changes in systematic risk when using bank return index as benchmark is superior to market return index. This study provides an intelligent and robust approach and suggests that future research should aim to overriding policy concerns related to systemic stability.

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Table 1: sample description: number of M&As deals

Country	Acquirers	Targets
Panel A: Breakdown by country		
Argentina	3	0
Austria	3	6
Belgium	2	9
Brazil	4	3
Canada	0	5
Chile	3	0
Colombia	1	0
Cyprus	1	0
Czech Republic	7	0
Denmark	2	0
France	6	8
Germany	4	4
Greece	2	2
Hong Kong	4	2
Hungary	3	1
India	0	1
Indonesia	6	0
Ireland-Rep	0	1
Israel	0	3
Italy	3	6
Luxembourg	2	0
Mexico	5	0
Netherlands	1	10
New Zealand	1	0
Norway	2	2
Peru	1	0
Philippines	3	0
Poland	6	0
Portugal	1	0
Romania	5	0
Russian Fed	1	0
Singapore	0	9
South Africa	2	1
South Korea	4	1
Spain	0	11
Switzerland	2	0
Sweden	0	3
Taiwan	1	0
Thailand	8	0
Turkey	4	1
United Kingdom	2	18
United States	9	7
Total	114	114
Panel B: Breakdown by region		
American	12	15
Asia	35	20
Africa	4	1
Europe	60	77
Middle East	3	1
Total	114	114
Panel C: Breakdown by year		
1998	14	
1999	18	
2000	14	
2001	19	
2002	5	
2003	10	
2004	13	
2005	21	
Total	114	

Table 2: statistics summary

Variables	Obs.	Mean	Median	Max	Min	Std	SD
Daily return	118210	0.0003	0.0000	0.2242	-5.0556	0.0337	-87.2252
World bank return	118210	0.0002	0.0006	0.0556	-0.0488	0.0097	-0.0757
Home bank return	118210	0.0004	0.0000	0.3546	-0.3248	0.0161	0.0629
Host bank return	118210	0.0005	0.0000	0.4052	-0.3388	0.0200	0.2591
World market return	118210	0.0002	0.0007	0.0404	-0.0442	0.0085	-0.1998
Home market return	118210	0.0003	0.0004	0.1953	-0.1259	0.0121	-0.1647
Host market return	118210	0.0003	0.0000	0.3222	-0.2262	0.0163	0.3606

Source: Daily return: DataStream, Mergent online, Yahoo Finance.

World bank return, Home bank return, Host bank return, World market return, Home market return, Host market return: DataStream, Yahoo Finance.

Table 3: the coefficients in (1)-(3) by cointegration analysis

Event No	Acquirer	Coefficients in (1)			Coefficients in (2)			Coefficients in (3)		
		λ_{world}	λ_{home}	λ_{host}	λ_{world}	λ_{home}	λ_{host}	λ_{world}	λ_{home}	λ_{host}
1	Banco Itau SA	(0.321)	(0.255)	(1.751)	(1.868)	(0.921)	0.609	2.088	0.951	(1.797)
2	Royal Bank of Scotland Group	0.590	1.208	(2.011)	2.758	9.171	(8.100)	(1.403)	(5.501)	3.912
3	Svenska Handelsbanken AB	(3.605)	6.162	(4.612)	(0.212)	1.976	0.079	1.632	0.300	1.179
4	ABN-AMRO Holding NV	2.096	(2.029)	(1.764)	4.967	(3.646)	(1.249)	(6.482)	1.599	4.146
5	Bank of Nova Scotia,Toronto	0.446	(0.422)	0.634	13.222	(10.936)	0.703	(59.786)	55.068	(1.759)
6	Citigroup Inc	30.782	(23.748)	1.510	109.297	(97.082)	0.320	(127.127)	112.783	0.375
7	Citigroup Inc	23.707	(17.883)	0.655	277.472	(237.423)	1.122	(98.166)	84.252	(0.580)
8	Royal Bank of Canada	17.903	2.644	(15.856)	135.433	(3.966)	(117.239)	23.580	(1.457)	(20.261)
9	Citigroup Inc	(47.917)	31.309	9.612	(191.894)	167.493	6.061	28.729	(25.254)	(0.964)
10	Banco Bradesco SA	(1.072)	0.462	(4.788)	3.299	0.304	(2.060)	2.252	(0.083)	(0.974)
11	Banco Itau SA	(0.286)	(0.111)	(0.165)	(24.180)	(2.339)	22.981	(33.316)	(2.995)	30.735
12	Royal Bank of Canada	(2.201)	(1.216)	2.431	(1.021)	(11.549)	9.672	(3.901)	(17.968)	17.465
13	JPMorgan Chase & Co	32.829	(24.949)	1.306	152.229	(133.056)	8.893	(239.983)	209.239	(14.429)
14	Citigroup Inc	147.568	(178.454)	6.779	168.996	(172.363)	(9.876)	25.114	(25.185)	(1.536)
15	Citigroup Inc	314.523	(410.138)	15.516	1037.249	(1313.687)	50.169	63.915	(79.545)	2.854
16	Toronto-Dominion Bank	(4.797)	(0.403)	6.754	51.059	5.259	(63.817)	16.786	2.059	(21.025)
17	Merrill Lynch & Co Inc	(1.516)	(0.306)	2.224	33.314	(48.211)	(2.880)	16.504	(24.254)	(0.842)
18	Bank of Nova Scotia,Toronto	(0.420)	0.028	(0.314)	(11.650)	24.753	(3.230)	(2.600)	6.148	(0.606)
19	DBS Bank	(8.810)	(0.624)	7.928	11.075	3.823	(9.678)	11.195	3.019	(8.590)
20	UOB	0.661	1.038	(1.091)	5.564	(5.391)	1.471	10.003	(10.390)	2.747
21	UOB	2.316	1.534	(1.476)	3.834	(0.654)	(1.010)	3.353	(0.890)	(0.888)
22	Hongkong & Shanghai Bkg Corp	(1.701)	0.888	0.236	(9.026)	4.240	1.541	(8.629)	4.008	1.538
23	Hongkong & Shanghai Bkg Corp	0.289	(0.008)	(0.186)	52.145	(47.466)	5.667	32.296	(29.757)	3.833
24	DBS Group Holdings Ltd	59.917	7.488	(56.310)	1.426	2.340	(1.306)	(4.405)	(1.219)	4.389
25	DBS Bank	2.834	0.301	(4.638)	(25.465)	16.200	(8.144)	1.603	(0.514)	0.316
26	UOB	(0.621)	1.700	(1.289)	(0.607)	0.877	(0.495)	(0.417)	0.298	(0.095)
27	UOB	0.566	0.173	(0.221)	(0.087)	0.583	(0.163)	(0.526)	0.608	0.039
28	UOB	0.157	0.222	(0.267)	(0.154)	0.229	(0.248)	(0.275)	0.114	0.069
29	UOB	(0.090)	0.022	0.029	0.299	(0.027)	(0.208)	12.362	(4.559)	(4.988)
30	Korea Exchange Bank	(3.244)	1.733	1.256	(7.751)	3.200	2.880	(8.692)	3.428	3.302
31	SBI	(2.974)	0.828	1.196	(14.032)	3.353	6.573	(17.699)	4.135	8.364
32	Societe Generale SA	0.395	(0.492)	0.122	38.482	(32.920)	(7.515)	(28.976)	24.773	4.736
33	ABN-AMRO Holding NV	1.151	(0.684)	0.014	7.694	(4.853)	(0.334)	6.498	(5.247)	(0.024)
34	Banco Bilbao Vizcaya SA	32.898	(20.355)	0.986	120.085	(108.180)	4.405	5.715	(5.850)	0.107
35	Banco Bilbao Vizcaya SA	0.395	(0.492)	0.122	63.581	(47.530)	18.151	(12.632)	9.366	6.431
36	ABN-AMRO Holding NV	0.936	(0.494)	0.162	(2.130)	6.049	(3.345)	(2.156)	4.117	(1.929)
37	Banco Bilbao Vizcaya SA	36.100	(25.387)	5.030	98.837	(78.699)	3.416	4.640	(4.385)	0.054
38	Deutsche Bank AG	1.603	(0.969)	(0.462)	(3.492)	4.950	(1.601)	(7.535)	10.128	(3.563)
39	ABN-AMRO Holding NV	1.419	(0.850)	(0.081)	10.941	(10.298)	(1.055)	30.701	(32.013)	(2.941)
40	Alpha Credit Bank	(7.330)	3.066	(1.044)	(8.890)	3.483	(1.700)	(17.271)	7.054	(4.430)

41	HSBC Holdings PLC{HSBC}	(0.799)	0.752	0.201	(10.613)	8.925	1.220	(13.010)	10.884	1.315
42	Fortis AG	1.437	(1.200)	0.127	(6.529)	5.108	6.590	(46.938)	30.726	37.223
43	Banco de Santander SA	(1.523)	1.832	(0.948)	(8.355)	7.456	(0.233)	(10.304)	8.420	(0.367)
44	Standard Chartered Bank PLC	(1.016)	19.739	(12.360)	(245.039)	255.902	(41.101)	(19.590)	20.851	(3.630)
45	Standard Chartered Bank PLC	(19.685)	(4.735)	7.329	(27.085)	24.128	1.664	(13.768)	11.907	0.969
46	Svenska Handelsbanken AB	53.258	(35.029)	115.800	13.736	(5.864)	(5.046)	12.497	(5.307)	(4.448)
47	HSBC Holdings PLC{HSBC}	0.579	0.410	(2.051)	(28.643)	30.916	0.851	(11.993)	12.679	0.640
48	HSBC Holdings PLC{HSBC}	60.033	37.431	(68.172)	(2.208)	7.169	(4.767)	(0.854)	7.389	(6.325)
49	KBC Bank & Insurance	6.610	(16.953)	2.152	0.963	(0.949)	0.216	0.506	(0.519)	0.188
50	Standard Chartered Bank PLC	(297.415)	98.154	54.813	(12.272)	14.765	0.208	(18.079)	23.683	(0.881)
51	Dexia SA	(16.854)	7.515	8.066	(9.151)	(0.620)	9.198	6.496	(0.210)	(6.060)
52	Deutsche Bank AG	2.870	(2.726)	2.000	(5.714)	6.753	(1.952)	1.129	(0.067)	(0.976)
53	Erste Bank	5.605	(2.171)	0.586	(3.090)	5.552	2.567	(3.460)	5.949	2.102
54	KBC Bank & Insurance	1.489	(0.798)	(0.536)	1.193	(2.159)	(0.464)	0.737	(1.368)	(0.435)
55	Dexia SA	0.314	(0.348)	0.612	(0.186)	(0.806)	1.324	(0.723)	(0.758)	1.204
56	ABN-AMRO Holding NV	(2.248)	1.874	(0.310)	(2.408)	2.744	0.100	(2.725)	3.244	0.514
57	Dexia SA	(7.901)	(1.105)	7.730	(1.932)	(3.523)	7.228	(1.232)	(2.446)	4.591
58	HSBC Holdings PLC{HSBC}	217.057	(141.246)	(91.768)	84.458	(137.260)	(11.888)	(13.288)	21.272	2.394
59	Standard Chartered PLC	(0.046)	(0.307)	2.156	3.305	30.419	(35.407)	1.030	16.980	(19.278)
60	Deutsche Bank AG	(2.641)	2.972	1.139	(7.586)	11.380	5.079	1.381	(0.637)	0.194
61	Standard Chartered PLC	(2.622)	10.299	(6.549)	(7.781)	45.722	(18.119)	(10.821)	62.597	(24.575)
62	HSBC Holdings PLC{HSBC}	(16.992)	12.628	6.350	(52.776)	148.061	(42.948)	(15.958)	45.505	(13.692)
63	ABN-AMRO Holding NV	0.423	6.279	(4.131)	20.750	6.435	(23.075)	16.537	4.850	(18.378)
64	Anglo Irish Bank Corp PLC	11.796	(0.214)	(8.391)	(7.544)	(6.602)	14.496	(13.649)	(8.042)	22.002
65	BBVA SA	1.771	(1.335)	(0.033)	(727.436)	901.295	(102.329)	(17.347)	20.537	(2.199)
66	Erste Bank	(3.255)	(8.589)	(2.590)	0.218	(0.657)	1.433	0.061	0.511	1.402
67	Fortis Bank(Fortis)	0.112	(1.266)	0.250	(5.660)	(1.356)	4.029	(5.390)	(0.966)	4.362
68	Svenska Handelsbanken AB	0.189	2.899	(2.304)	(6.349)	3.927	0.144	(6.278)	3.517	0.319
69	BNP Paribas SA	(3.250)	(0.615)	3.005	(19.988)	(1.784)	17.854	(34.561)	(5.673)	34.158
70	Commerzbank AG	0.378	0.275	(1.049)	(30.412)	16.339	(3.827)	(10.985)	5.998	(1.016)
71	Societe Generale SA	(0.070)	(0.383)	0.024	(44.802)	31.938	(7.082)	80.526	(57.293)	12.237
72	BNP Paribas SA	(0.636)	0.680	0.030	(39.195)	29.249	(1.774)	80.068	(60.699)	3.689
73	HSBC Bank PLC	8.421	(12.031)	(0.021)	(11.606)	10.849	0.879	15.111	(19.844)	(0.640)
74	Unicredito Italiano SpA	(0.640)	0.353	(0.058)	(6.611)	5.151	(0.175)	4.331	(3.755)	(0.074)
75	BBVA SA	(1.803)	1.725	(0.739)	(4.792)	7.148	(4.390)	(3.510)	5.635	(3.545)
76	BNP Paribas SA	0.288	1.250	(1.818)	(13.230)	(6.992)	17.665	(28.005)	(17.802)	41.456
77	BBVA SA	(2.067)	1.075	(0.360)	7.992	(6.575)	0.115	6.301	(4.757)	(0.267)
78	Erste Bank	1.043	(0.724)	(0.913)	(3.179)	5.100	0.566	(2.164)	3.368	0.444
79	HSBC Holdings PLC{HSBC}	0.926	(0.682)	0.354	3.490	(3.203)	0.698	(139.936)	127.789	(13.285)
80	Banco Popular Espanol SA	(0.847)	0.916	(0.833)	(1.279)	1.615	(1.078)	1.663	(2.164)	0.050
81	Sanpaolo IMI Bank Intl SA	(1.303)	1.432	(0.483)	(14.429)	11.001	1.242	(12.885)	9.889	1.253
82	HSBC Holdings PLC{HSBC}	(7.564)	9.434	2.834	13.390	(9.612)	(4.607)	(19.890)	16.075	5.372
83	Unicredito Italiano SpA	1.675	(0.746)	0.082	37.639	(31.046)	2.315	(43.782)	37.045	(3.090)
84	HBOS PLC	(40.463)	49.774	24.974	13.331	(4.866)	(13.220)	9.832	(3.875)	(9.830)
85	Standard Chartered PLC	2.929	(0.878)	(2.248)	(24.436)	23.331	(1.719)	5.267	(4.429)	(0.012)
86	Erste Bank	(0.066)	0.705	0.063	(0.431)	0.173	1.470	(0.701)	0.420	0.502
87	National Bank of Greece SA	0.694	(0.115)	(0.726)	3.948	(3.404)	(1.117)	2.014	(1.988)	(0.543)
88	ABN-AMRO Holding NV	(0.177)	(0.675)	0.730	(0.295)	(5.267)	5.140	(0.908)	8.834	(7.614)
89	Societe Generale SA	(0.205)	0.532	(0.246)	(1.344)	1.690	(0.400)	(3.964)	4.093	0.850
90	BBVA SA	(1.734)	1.091	(0.031)	(14.344)	24.858	(9.509)	(10.377)	18.632	(7.058)
91	Societe Generale SA	(0.789)	0.826	0.124	14.644	(18.113)	(1.951)	184.038	(225.769)	(30.132)
92	OTP Bank	(0.010)	0.007	0.006	(3.109)	3.555	(1.522)	(3.047)	3.471	(1.506)
93	BBVA SA	(6.944)	0.491	8.104	(58.968)	(21.920)	92.283	8.415	2.982	(12.864)
94	Barclays PLC	(9.243)	3.349	4.216	(21.007)	20.205	8.605	(15.964)	15.941	6.534
95	Societe Generale SA	(3.854)	4.458	(0.515)	(1.012)	7.729	(5.549)	(0.967)	11.663	(8.873)
96	Standard Chartered PLC	14.394	(0.960)	(10.122)	(4.518)	(13.117)	10.424	20.414	60.060	(48.913)
97	BBVA SA	2.034	(2.878)	0.852	5.794	(10.138)	4.832	4.137	(6.781)	3.082
98	Fortis Group NV	0.446	(0.740)	(0.251)	(0.259)	(1.335)	0.366	(5.308)	2.727	3.532
99	Unicredito Italiano SpA	(1.363)	2.296	(0.641)	(3.447)	5.095	(1.544)	(3.165)	5.134	(1.403)
100	Unicredito Italiano SpA	35.516	(318.482)	224.898	(5.788)	5.165	0.853	(24.127)	23.233	4.696
101	Unicredito Italiano SpA	(3.547)	2.857	0.664	(5.309)	4.877	0.757	(8.312)	8.812	0.983
102	DnB NOR Bank ASA	0.102	(0.030)	(0.048)	1.560	(1.161)	0.457	1.697	(1.307)	0.465
103	ABN-AMRO Holding NV	2.248	(0.967)	(0.888)	(14.955)	3.017	7.472	(11.519)	2.753	5.497
104	Fortis Commercial Private Bkg	(2.930)	0.329	5.283	(3.583)	(2.552)	7.609	11.957	19.937	(34.638)
105	ABN AMRO Bank NV	1.609	(0.064)	(1.896)	3.546	(1.499)	(2.957)	5.755	(2.000)	(5.284)

106	ABN AMRO Bank NV	1.609	(0.064)	(1.896)	3.546	(1.499)	(2.957)	5.755	(2.000)	(5.284)
107	DnB NOR Bank ASA	0.149	(0.136)	(0.029)	0.869	(1.326)	(0.105)	3.528	(3.613)	(0.242)
108	Erste Bank	1.428	(1.884)	1.611	(46.389)	38.161	(3.308)	25.660	(20.234)	0.993
109	ANZ Banking Group Ltd	(2.608)	1.413	0.851	65.547	(72.167)	(12.835)	6.727	(7.184)	(1.141)
110	Standard Bank Invest Corp Ltd	(33.176)	(1.501)	28.310	(73.608)	21.025	38.858	(38.367)	10.849	20.093
111	Bank Hapoalim BM	(0.252)	0.581	(0.371)	(0.249)	0.600	(0.527)	(31.051)	(32.530)	87.951
112	Akbank TAS	(1.672)	0.569	1.107	(15.597)	9.367	15.267	(103.359)	49.828	107.152
113	Bank Hapoalim BM	0.719	(0.637)	0.147	0.869	1.590	(0.161)	0.902	1.223	(0.248)
114	Bank Leumi Le Israel BM	(0.148)	1.049	(0.668)	(3.556)	11.250	(4.817)	(13.868)	35.401	(14.391)

Table 4: the effects of changes in systematic risk by cointegration analysis

Equation	λ_{home}	λ_{world}	λ_{host}
Panel A: Breakdown by M&As deals			
1	58	58	58
2	52	45	56
3	49	49	56
Panel B: Breakdown by M&As percentage			
1	50.88%	50.88%	50.88%
2	45.61%	39.47%	49.12%
3	42.98%	42.98%	49.12%

Note: The deals and percentage indicate significantly above 5%.

λ_{home} shows the negative significantly effect of M&As transactions and percentage.

λ_{world} and λ_{host} shows the positive significantly effect of M&As transactions and percentage, separately.

Table 5: the rankings of acquirer events by web-based GRA analysis

GRA Ranking	Results Based on the Coefficients of (1)		Results Based on the Coefficients of (2)		Results Based on the Coefficients of (3)		Results Based on the Coefficients of (1-3)	
	Event No	GAMMA	Event No	GAMMA	Event No	GAMMA	Event No	GAMMA
1	100	1.0000	15	1	111	1	15	1.000
2	15	0.8328	7	0.6106	71	0.9184	100	0.676
3	14	0.6288	13	0.5761	15	0.8768	14	0.621
4	46	0.5802	93	0.5633	72	0.8742	46	0.536
5	37	0.3808	34	0.557	76	0.8661	111	0.509
6	13	0.3710	14	0.5558	69	0.8115	76	0.479
7	6	0.3685	35	0.5515	12	0.8026	37	0.472
8	34	0.3645	6	0.5459	11	0.7965	34	0.472
9	58	0.3622	37	0.5449	64	0.796	71	0.467
10	7	0.3547	23	0.5314	23	0.7937	69	0.462
11	49	0.3447	58	0.5272	91	0.7909	23	0.459
12	110	0.3413	11	0.5268	108	0.7599	11	0.458
13	73	0.3356	110	0.5258	9	0.7592	72	0.457
14	57	0.3242	76	0.5241	39	0.7591	12	0.457
15	16	0.3237	69	0.5216	14	0.7524	64	0.450
16	52	0.3234	64	0.5213	42	0.7482	110	0.445
17	93	0.3234	83	0.5199	17	0.7457	91	0.441
18	19	0.3232	96	0.5179	73	0.7397	35	0.437
19	53	0.3220	12	0.5175	112	0.7392	58	0.433
20	104	0.3214	112	0.5172	20	0.7389	17	0.432
21	97	0.3209	17	0.5141	97	0.7292	39	0.431
22	108	0.3206	51	0.5127	110	0.7268	112	0.430
23	45	0.3196	57	0.5123	2	0.7251	73	0.430
24	12	0.3187	104	0.5122	57	0.7244	42	0.429

25	59	0.3186	97	0.512	24	0.7181	97	0.426
26	69	0.3183	88	0.5101	67	0.7164	57	0.426
27	66	0.3182	109	0.5095	34	0.715	49	0.422
28	17	0.3177	42	0.5086	33	0.7144	93	0.422
29	65	0.3171	103	0.5082	31	0.7131	20	0.421
30	42	0.3170	5	0.5079	77	0.7124	108	0.416
31	83	0.3165	31	0.5071	85	0.712	67	0.415
32	67	0.3164	67	0.5064	109	0.7117	109	0.413
33	79	0.3164	20	0.5062	37	0.7116	103	0.413
34	88	0.3163	91	0.5056	4	0.7106	31	0.413
35	5	0.3163	32	0.5051	74	0.7098	33	0.413
36	39	0.3162	60	0.505	103	0.7093	66	0.411
37	55	0.3160	94	0.505	107	0.7079	77	0.410
38	33	0.3159	77	0.5049	98	0.7075	53	0.409
39	113	0.3158	39	0.5046	3	0.7075	55	0.409
40	36	0.3158	79	0.5041	66	0.7065	4	0.409
41	38	0.3157	33	0.5039	55	0.7063	98	0.408
42	103	0.3154	66	0.5039	102	0.7062	107	0.408
43	32	0.3154	55	0.5037	80	0.7053	102	0.408
44	35	0.3154	86	0.5037	25	0.7043	74	0.406
45	54	0.3153	53	0.5036	60	0.7036	60	0.406
46	4	0.3150	30	0.5034	35	0.7032	86	0.406
47	98	0.3150	102	0.5029	87	0.7025	54	0.405
48	71	0.3147	49	0.5024	49	0.7025	87	0.405
49	107	0.3144	98	0.5024	30	0.7015	30	0.405
50	112	0.3144	1	0.5023	86	0.7014	52	0.405
51	78	0.3142	107	0.5019	21	0.7009	113	0.405
52	29	0.3142	4	0.5016	54	0.7008	28	0.404
53	92	0.3142	54	0.5016	28	0.7001	27	0.404
54	102	0.3142	87	0.5015	27	0.699	80	0.403
55	23	0.3141	29	0.5014	26	0.6989	2	0.403
56	27	0.3140	27	0.5013	46	0.6987	21	0.403
57	11	0.3139	113	0.5013	53	0.6985	29	0.402
58	28	0.3136	3	0.5013	113	0.6984	78	0.402
59	87	0.3135	28	0.5012	10	0.6981	94	0.401
60	86	0.3134	21	0.5011	52	0.6968	89	0.401
61	18	0.3133	22	0.501	78	0.6954	26	0.401
62	31	0.3133	111	0.5007	56	0.6953	85	0.401
63	85	0.3132	56	0.5007	29	0.6949	1	0.400
64	74	0.3132	78	0.5007	89	0.6944	22	0.400
65	41	0.3131	26	0.5006	1	0.6925	56	0.400
66	72	0.3130	101	0.5006	22	0.6923	51	0.398
67	89	0.3129	100	0.5005	94	0.6904	3	0.397
68	91	0.3128	89	0.5004	68	0.6899	10	0.397
69	111	0.3126	82	0.4996	18	0.6861	92	0.396
70	22	0.3123	24	0.4996	92	0.6848	68	0.395
71	70	0.3122	68	0.4996	101	0.6835	101	0.395
72	109	0.3121	80	0.4994	105	0.6829	105	0.394
73	30	0.3120	10	0.4992	106	0.6829	106	0.394
74	105	0.3119	41	0.4992	99	0.6829	36	0.394
75	106	0.3119	74	0.4988	36	0.6828	41	0.393
76	90	0.3116	105	0.4983	82	0.68	99	0.392
77	114	0.3115	106	0.4983	81	0.6779	81	0.391
78	20	0.3113	46	0.4982	51	0.6775	45	0.391
79	1	0.3111	73	0.4981	41	0.6767	18	0.391
80	94	0.3111	92	0.4979	43	0.6752	88	0.390
81	21	0.3111	43	0.4979	70	0.6745	43	0.389
82	80	0.3109	81	0.4979	45	0.6728	25	0.389
83	77	0.3107	38	0.4975	47	0.6723	82	0.389
84	81	0.3106	99	0.4975	75	0.6713	32	0.388
85	60	0.3106	40	0.4963	58	0.667	19	0.387
86	47	0.3103	50	0.4962	84	0.6664	38	0.387
87	56	0.3097	52	0.4961	19	0.6653	75	0.385
88	76	0.3094	36	0.4949	100	0.6616	47	0.384
89	75	0.3094	45	0.493	38	0.6606	70	0.383

90	2	0.3093	48	0.4925	48	0.6581	7	0.378
91	101	0.3093	75	0.4925	32	0.6535	40	0.375
92	26	0.3092	95	0.4915	88	0.6497	95	0.369
93	99	0.3091	114	0.4913	40	0.6491	83	0.368
94	43	0.3090	47	0.4902	50	0.6426	24	0.363
95	25	0.3072	18	0.4893	65	0.6416	90	0.360
96	51	0.3070	85	0.4888	93	0.6404	84	0.351
97	64	0.3068	19	0.4884	95	0.6396	9	0.349
98	68	0.3063	2	0.488	44	0.6318	5	0.343
99	96	0.3061	70	0.4856	90	0.6289	63	0.341
100	95	0.3048	84	0.4848	8	0.6215	114	0.341
101	10	0.3040	72	0.4841	63	0.6171	104	0.332
102	40	0.3032	25	0.4801	16	0.6066	59	0.317
103	82	0.3018	90	0.4789	83	0.5822	6	0.311
104	63	0.2987	108	0.4784	59	0.5816	16	0.301
105	62	0.2971	71	0.4743	114	0.5662	48	0.300
106	3	0.2952	63	0.4674	62	0.5534	61	0.274
107	8	0.2927	61	0.4624	5	0.5419	96	0.271
108	61	0.2869	59	0.4368	104	0.5063	62	0.263
109	44	0.2648	9	0.4308	61	0.4812	44	0.238
110	84	0.2604	16	0.3934	7	0.4519	79	0.217
111	9	0.2551	62	0.3899	96	0.3846	8	0.213
112	24	0.2283	44	0.3312	6	0.3711	50	0.199
113	48	0.1656	8	0.2836	79	0.2778	13	0.131
114	50	0.0000	65	0	13	0	65	0.000

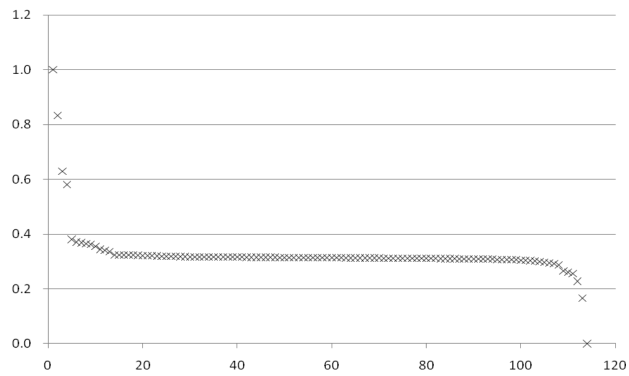

Fig. 1 distribution of grey relationship relative to event number based on (1)

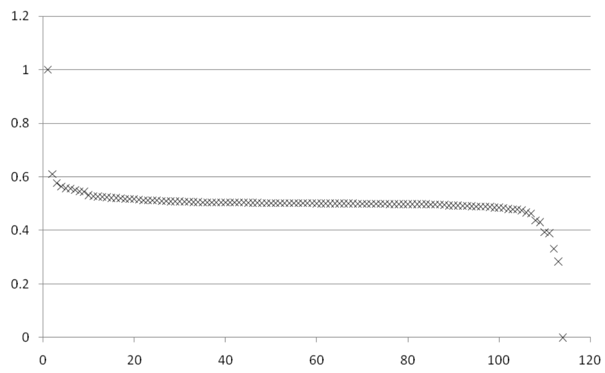

Fig. 2 distribution of grey relationship relative to event number based on (2)

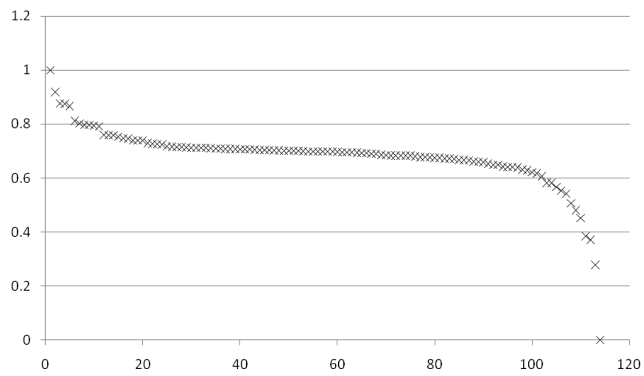

Fig. 3 distribution of grey relationship relative to event number based on (3)

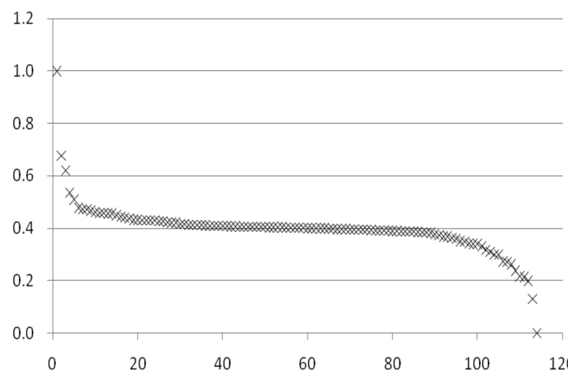

Fig. 4 distribution of grey relationship relative to event number based on (1) to (3)