Contents

A Note from the Editor's Board

The YMC Management Review has been published for seven volumes so far. And the iFAIRS 2014 conference had been hold at Tokyo JAPAN on 15 June 2014. I would like to thank the National Kaohsiung First University of Science & Technology for assisting this international conference.

The YMC Management Review publishes two numbers each year. The first number publishes the cooperation of holding the iFAIRS conference in English. The second number, discussed mainly in Mandarin, publishes topics about practical management. The editor's board welcomes all articles that are ready for submission, regarding the practical management discussions or management cases. Furthermore, we hope the YMC Management Review could be included as a member of the Social Science Citation Index (SSCI) in the near future.

I am pleased to announce that this number of the YMC Management Review contains five papers which is the most plentiful number of English issue of YMCMR.
On the Comparison of Ordinary Linear and Poisson Log-linear Model discusses the residential mortgage Loans in TAIWAN, *An Empirical Investigation of Mediating Effect on Corporate Social Responsibility and Financial Performance* discusses the mediating effect on corporate social responsibility from intangible assets perspective. *Impacts of Knowledge Leadership and the Characteristics of Organizational Structure on Employee Learning Motivation* discusses in the Cultural and Creative Industries in TAIWAN. *Does Noise Matter on Hedging Effectiveness?* discusses hedging effectiveness from Taiwan stock market. *The Discriminants to Avoid Erroneous GM(1,1) Prediction* is a newly solution seeking in grey forecasting model. Each paper is worth reading.

Once again, we invite you to submit your paper to the YMC Management Review any time, and we hope to meet you in the iFAIRS conference every year in the future.

Editor-in-Chief

Alex Kung-Hsiung CHANG

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On the Comparison of Ordinary Linear and Poisson Log-linear Model for Residential Mortgage Loans

Tsung-Hao CHEN *

Assistant Professor, Department of Business Administration, Shu-Te University, Kaohsiung city, Taiwan, R.O.C.

* Corresponding author: thchen@stu.edu.tw

ABSTRACT

When the response variable had a normal distribution we used ordinary linear regression model to analyze data set by linking a set of explanatory variables. If the response variable is count data, counts are all positive integers, a Poisson regression model is suitable for the discrete, non-negative integer values and highly-skewed distribution of residential mortgage loans data.

In this study, we examine the data of residential mortgage loans, its shape look like Poisson distribution. So we test the distribution of scores by the Kolmogorov-smirnov one-sample test, the results indicate that the data came from a population with the Poisson distribution. Then detecting multicollinearity, we find no multicollinearity is evident by tolerance and variance inflation factor (VIF).

Although many researchers analyzed count data by ordinary linear regression, comparing finally above two previous regression analyses, all the estimate values of ordinary linear regression model are large Poisson loglinear model, but intercept is not significant and illegitimate. Therefore, we find that Poisson loglinear model has the advantage of being stably suitable for the discrete data of residential mortgage loans.

Keywords: *Residential Mortgage Loans, Default, Tolerance, Poisson Log-linear Model*

1. Introduction

When a potential debtor asks for credit, creditors evaluate the probability of default to decide whether to lend the funds and at what interest rate. Thus accurately assessing a debtor's likelihood to default or not. This role acts as an important function for the continued competitiveness of creditors. Therefore, the creditor generally collateralizes the debtor's house to maintain low loan-to-value (LTV) and so reduces the default risk (Marrison, 2002).

Many studies have attempted to monitor and examine the factors associated with the default of a residential mortgage. Such as incomes of family, education, grace period and the present value of mortgage payments, also taking into consideration LTV ratio, home equity and unemployment rates, similarly, the effects of counseling on default, and divorce rates are also significant to mortgage default (Green and Shoven, 1986;Lawrence et al., 1992; Deng et al., 1996, 1997, and 2000; Kau and Keenan, 1999; Ciochetti et al., 2001; Marrison, 2002; Lambrecht et al., 2003; Hartarska and Gonzalez-Vega, 2005, 2006). Ambrose, Capone, and Deng (2001) redefined the boundary conditions for optimal default exercise to look at the economic dynamics leading to optimal default timing for mortgage foreclosure. Ong, Neo, and Tu (2007) showed that price expectations, volatility and equity losses are influential factors for individual households, with past price movement being the most important of these. Chen and Chen (2010) discussed how these factors influenced mortgages prior to foreclosure and how they are correlated with location.

Even though many previous studies on residential mortgage default behaviors have been undertaken, less research was found to focus specifically on the measure of the predictive adequacy. This study attempts to search for an appropriate model to raise the predictive accuracy for the discrete data of residential mortgage loans. The remnants of this paper are organized as follows. Section 2 introduces research framework. Section 3 gives the empirical analysis using Poisson loglinear model as a comparison. Section 4 concludes this study.

2. Research Framework

From the central limit theorem that in big samples the sampling distribution tends to be normal and as our sample gets bigger then we can be more confident that the sampling distribution is normally distributed. In many statistical tests we assume that the sampling distribution is normally distributed, but we still need to sure whether or not an assumption has been met. We can't simply look at its shape and see whether it is normally distributed.

In previous study, many researchers analyzed count data by ordinary linear regression, but Poisson regression has the advantage of being precisely suitable for the discrete, often highly-skewed distribution of the dependent variable. The Poisson loglinear model is a method appropriate for dependent variables that have only non-negative integer values (Allison, 2005).

2.1 The Kolmogorov-smirnov one-sample test

The Kolmogorov-smirnov one-sample test (Walker, 2002) compares the observed cumulative distribution function of a variable with a specified theoretical distribution, which may be normal, uniform, Poisson, or exponential distribution. That is, the Kolmogorov-smirnov one-sample test is designed to test whether the distribution of the members a single group differs significantly from a normal, uniform, Poisson, or exponential distribution (George, 2008).

The test is usually a measure of how close the model distribution function is to the empirical distribution function. When the model's distribution function is close to the empirical distribution function, it is difficult to make small distinctions (Klugman,et al., 2008). The hypotheses are summarized as follows:

Null hypothesis

H0：The data came from a population with the Poisson distribution.

Alternative hypothesis

H1：The data did not come from a population with the Poisson distribution.

Let t be the left truncation point and let μ be the right censoring point. Then, the test statistic is

$$D = \max_{t \le x \le \mu} \left| F_n(x) - F^*(x) \right|. \quad (4)$$

where

$F_n(x)$ is the empirical distribution function

$F^*(x)$ is the model distribution function.

$$F^*(x) = \begin{cases} 0, & x<t, \\ \dfrac{F(x)-F(t)}{1-F(t)} & x \ge t, \end{cases}$$

2.2 The Poisson loglinear model

(1) Probability for the Poisson distribution

The Poisson distribution is unimodal and skewed to the right over the possible values of y (Agresti, 2007). Let y be a variable that can have only non-negative integer values, the probability mass function of y defined as follows.

$$\Pr(y=k)=\frac{\lambda^k e^{-\lambda}}{k!}=\exp(-k)\left(\frac{1}{k!}\right)\exp(k\log\lambda),\ k{=}0,1,2...$$

where λ is the expected value of y and $k!$, k is the non-negative integer values.

(2) log-likelihood function

We use the method of Maximum Likelihood (MLE) to estimate the parameter of Poisson distribution, it is showed as:

The likelihood function of Poisson model (Klugman,et al., 2008) is

$$L=\prod_{k=0}^{\infty}\left(\frac{e^{-\lambda}\lambda^k}{k!}\right)^{n_k}$$

We can find the log-likelihood function

$$\begin{aligned} l &= \sum\nolimits_{k=0}^{\infty} n_k[-\lambda + k\ln\lambda - \ln k!] \\ &= -n\lambda + \sum_{k=0}^{\infty} k\cdot n_k \ln\lambda - \sum_{k=0}^{\infty} n_k \ln k! \end{aligned}$$

where $n=\sum\nolimits_{k=0}^{\infty} n_k$ is the sample size.

Differentiating the log-likelihood function with respect to λ , we obtain

$$\begin{aligned} &\frac{dl}{d\lambda} = -n + \sum_{k=0}^{\infty}\frac{k\cdot n_k}{\lambda} \\ &\Rightarrow -n + \sum_{k=0}^{\infty}\frac{k\cdot n_k}{\lambda} = 0 \\ &\Rightarrow \lambda = \sum_{k=0}^{\infty}\frac{k\cdot n_k}{n} = \bar{y} = \mathrm{var}(y) \end{aligned}$$

So

$$MLE(\lambda)=\frac{\sum_{k=0}^{\infty}n_k\cdot k}{\sum_{k=0}^{\infty}n_k}=\frac{\sum_{k=0}^{\infty}n_k\cdot k}{n}=\overline{y}=\mathrm{var}(y)$$

where k = 0,1,2,..., n_k is the total numbers when happen k.

(3) The Poisson loglinear model

A Poisson loglinear model is a generalized linear model that assumes a Poisson distribution for y and uses the log link function (Agresti, 2007). Since λ can't be less than 0, it is standard to let λ be a loglinear function of x variables. The Poisson loglinear model has form

$$\log\lambda_i=\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+...+\beta_kX_{ik}$$

The mean satisfies the exponential relationship

$$\lambda_i=\exp(\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+...+\beta_kX_{ik})$$

A one-unit increase in xik has a multiplicative impact of e^{β_k} on λ_i. If β =0, then the multiplicative factor is 1, that is, the mean of y does not change as x changes. If β >0, then e^{β} >1 and the mean of y increases as x increases. While β <0, the mean of y decreases as x increases.

3. Analytical Results

For a Poisson loglinear model, the dependent variable is classified into five groups based on the range that borrowers performed records of the principle and interest. We studied a mortgage data that was collected in this study was all of individual residential loans originated in 1990 to 2005. The original mortgage data was collected from a local bank in Taiwan, this data included 2791 performing records during the observance period. The censoring time was the end of 2005.

3.1 Variables and explanations

The variables of our study are shown in **Table 1** including one dependent variable and eight independent variables. There are possibly eight factors influencing the default of residential mortgages. In this situation, the predictors are sex (X1), the balance of mortgage loans (X2), age (X3), years of job (X4), loan to value ratio (X5), package deal (X6), grace period(X7), marriage term (X8), and response outcome (Y) is a count of the range of performing records of residential mortgages loans.

Table 1 Variables and Explanations

variables	explanations
dependent	
Y-the range of default	The range of delinquency from 0 to 5
independent	
X_1-sex	Dummy variables; male = 1, female =0
X_2-the balance of mortgage loans	The monetary amount of mortgage loans
X_3-age	The age of borrowers
X_4-years of job	the years of job experience
X_5-loan to value ratio	The ratio of original loan size to original housing price (individual data)
X_6- package deal	Dummy variables; with package deal = 1, otherwise = 0
X_7- grace period	The grace period (years) of mortgage loan
X_8-marriage term	Dummy variables; married=1, otherwise = 0

3.2 Descriptive statistics and graph

We discovered that frequency distributions and graphs are a useful way to look at the shape of a distribution. To describe the characteristics of the data we should select the central tendency and measures of variability. To check whether a distribution of scores is normal or not, we need to look at the values of kurtosis and skewness. The values of skewness and kurtosis should be zero in a normal distribution. Positive values of skewness indicate a pile-up of scores on the left of the distribution, whereas negative values indicate a pile-up on the right. A distribution with positive kurtosis has many scores in the tails and is pointy. In contrast, negative values indicate a flat and light-tailed distribution.

From table 2 and figure 1, we can see that, on average, the mean of default was 1.4826 and kurtosis (0.012) is very close to zero, but the skew value (0.653) is positive and large. This positive value of skewness indicates a pile-up of scores on the left of the distribution, its shape look like Poisson distribution. So we need to examine whether a distribution of scores is normal or not.

Table 2 Descriptive statistics

N	Valid	2791
	Missing	0
Mean		1.4826
Std. Deviation		1.20734
Skewness		.653
Std. Error of Skewness		.046
Kurtosis		.012
Std. Error of Kurtosis		.093

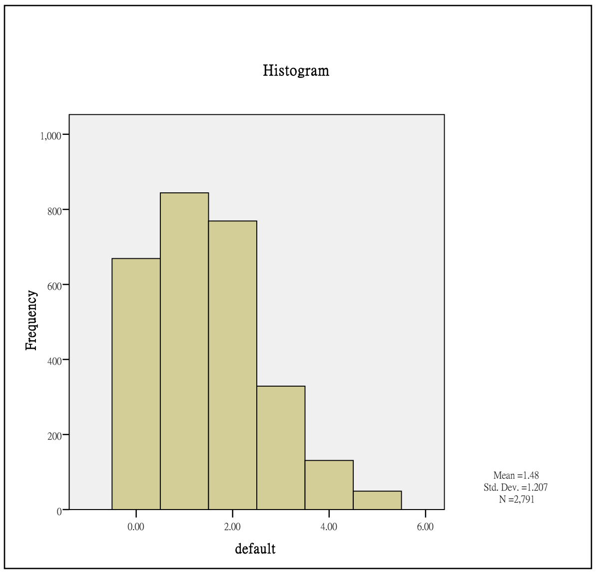

Figure 1 A positively skewed distribution

3.3 The Kolmogorov-smirnov one-sample test

Testing the Kolmogorov-smirnov one-sample test to sure whether the dependent variable y fit normal, uniform, Poisson, or exponential distribution. In Table 3 to Table 6, only Table 5 indicates that the dependent variable y has coefficients of 1.139. Associated p-value is 0.149 by Kolmogorov-Smirnov Z analysis, suggesting that the data came from a population with the Poisson distribution. That is, these measurement results indicate that the assumption of Poisson distribution is valid (see Table 5). For other Tables, we can find that all p-value are less than 0.05, the K-S test is highly significant, indicating a deviation from normal, uniform, and exponential distribution respectively.

Table 3 One-Sample Kolmogorov-Smirnov Test - normal distribution

sorts		values
N		2791
Normal Parameters(a,b)	Mean	1.4826
	Std. Deviation	1.20734
Most Extreme Differences	Absolute	.197
	Positive	.197
	Negative	-.124
Kolmogorov-Smirnov Z		10.430
Asymp. Sig. (2-tailed)		.000

a Test distribution is Normal.

b Calculated from data.

Table 4 One-Sample Kolmogorov-Smirnov Test 2- uniform distribution

sorts		values
N		2791
Uniform Parameters(a,b)	Minimum	.00
	Maximum	5.00
Most Extreme Differences	Absolute	.418
	Positive	.418
	Negative	-.018
Kolmogorov-Smirnov Z		22.063
Asymp. Sig. (2-tailed)		.000

a Test distribution is Uniform.

b Calculated from data.

Table 5 One-Sample Kolmogorov-Smirnov Test 3- Poisson distribution

sorts		values
N		2791
Poisson Parameter(a,b)	Mean	1.4826
Most Extreme Differences	Absolute	.022
	Positive	.013
	Negative	-.022
Kolmogorov-Smirnov Z		1.139
Asymp. Sig. (2-tailed)		.149

a Test distribution is Poisson.

b Calculated from data.

Table 6 One-Sample Kolmogorov-Smirnov Test 4- exponential distribution

sorts		values
N		2791
Exponential parameter.(a,b)	Mean	1.9500
Most Extreme Differences	Absolute	.445
	Positive	.445
	Negative	-.086
Kolmogorov-Smirnov Z		20.506
Asymp. Sig. (2-tailed)		.000

a Test Distribution is Exponential.

b Calculated from data.

3.4 Fitting Poisson loglinear model

This study was conducted to explore whether eight factors influenced the performing records of residential mortgages and all are considered in the Poisson loglinear model. For count response outcome like this data, we can use Poisson loglinear model to see how the outcome (Y) might depend on the values of those eight predictors. This model the natural logarithm of the expected value of response Y as

$$\log(E(Y=k)) = \beta_0 + \beta_1 x_5 + \beta_2 x_6 + \beta_3 x_9 + \ldots + \beta_8 x_{20}$$

Where

$$E(Y=k) = e^{\beta_0 + \beta_1 x_5 + \beta_2 x_6 + \beta_3 x_9 + \ldots + \beta_8 x_{30}}, k = 0,1,2,\ldots,8.$$

We first fit a Poisson loglinear model to these data using all eight available predictors. There are two high individual p-values in the complete model that suggest two predictors may be redundant and can be remove from the model of following eight indicator variables: X1, X2, X3, X4, X5, X6, X7 and X8. The reduced Poisson loglinear model has a reasonable fit to the data that all the p-values of individual variables are less than 0.05. Thus the results are as follows:

$$\begin{aligned}&\log(\mathrm{E}(\mathrm{Y}=k)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_5 x_5 + \beta_7 x_7 + \beta_8 x_8 \\ &= -0.5884 - 0.0835 x_1 + 0.0003 x_2 + 0.0163 x_3 + 0.0063 x_5 + 0.0508 x_7 - 0.1897 x_8\end{aligned}$$

From the Table 7, all the variables are highly significant. Female's default rate is 8% lower, on average, than those male; the default rate of married is 17% lower than single. On the other hand, consider the estimate β_1 =0.0163 for X=age. This means that if the age of borrowers increases by one year, then the natural logarithm of the expected range of default will increase by 0.0163, and the expected range of default will be multiplied by exp (0.0163)=1.0164. That is, the expected range of default increases 1.64% when the age of borrowers increases one year; the expected range of default increases5.21% when the grace period of borrowers increases one year.

Table 7 the predictive diagnostic of ROC curve

Explanatory variable	Complete model		Reduced model	
	esimate	p-values	esimate	p-values
Intercept	-0.5930	<0.0001***	-0.5884	<0.0001***
X_1-sex	-0.0841	0.0072**	**-0.0835**	0.0076**
X_2-balance of mortgage loans	0.0003	0.0004***	0.0003	0.0004***
X_{3-} age	0.0165	<0.0001***	0.0163	<0.0001***
X_4-years of job	-0.0000	0.9913	deleted	deleted
X_5-loan to value ratio	0.0061	0.0001***	0.0063	<0.0001***
X_6- package deal	0.0146	0.6772	deleted	deleted
X_7- grace period	0.0544	<0.0001***	0.0508	<0.0001***
X_8-marriage term	-0.1886	<0.0001***	**-0.1897**	<0.0001***

Note: *p<0.l; **P<0.05; ***P<.001.

3.5 Diagnosis of multi-collinearity

Mendard (1995) suggested that a tolerance of less than 0.20 is cause for concern and a tolerance of less than 0.10 certainly presents a serious multicollinearity problem. Burns and Burns (2008) suggested that a maximum VIF value in excess of 10 is frequently taken as an indication that multicollinearity may be unduly influencing the least squares estimates. Table 4 shows the analytical results of detecting multicollinearity. As shown in Table 4, the column, labeled as tolerance for the diagnostic of multicollinearity, has values that are all more than 0.8, and the column, labeled as variance inflation factor (VIF), has values that are all less than .1.5. Therefore, no multicollinearity is evident.

Table 8 The diagnosis of multicollinearity

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Tolerance	Variance Inflation
Intercept	1	0.06397	0.19728	0.32	0.7458	.	0
X1	1	-0.12424	0.04468	-2.78	0.0055	0.99357	1.00647
X2	1	0.000605	0.000152	3.98	<.0001	0.89417	1.11835
X3	1	0.02529	0.00313	8.07	<.0001	0.82401	1.21358
X5	1	0.00817	0.00209	3.91	<.0001	0.88766	1.12656
X7	1	0.07979	0.01617	4.93	<.0001	0.95766	1.04421
X8	1	-0.28570	0.05162	-5.53	<.0001	0.84251	1.18693

3.6 Comparing Poisson loglinear model and ordinary linear regression model

Summarizing two previous regression analysis (Table 7 and Table 8), by using the final method, satisfactory results can be achieved. All the estimate values of ordinary linear regression model are large Poisson loglinear model, but intercept is not significant and illegitimate. Although many researchers analyzed count data by ordinary linear regression, Poisson regression has the advantage of being precisely suitable for the discrete (Allison, 1999). Therefore, by using Poisson loglinear model method to highly-skewed distribution and non-negative integer values of the dependent variable, you would see the results from using Poisson loglinear model method are more suitable than the original module.

Table 9 comparison of Poisson loglinear model and ordinary linear regression model

Explanatory variable	**Poisson loglinear model**		**Ordinary linear regression**	
	esimate	p-values	esimate	p-values
Intercept	-0.5884	<0.0001***	**0.06397**	**0.7458**
X_1-sex	**-0.0835**	0.0076**	**-0.1242**	0.0055**
X_2-balance of mortgage loans	0.0003	0.0004***	0.0006	<0.0001***
X_{3-} age	0.0163	<0.0001***	0.0253	<0.0001***
X_5-loan to value ratio	0.0063	<0.0001***	0.0082	<0.0001***
X_7- grace period	0.0508	<0.0001***	0.0798	<0.0001***
X_8-marriage term	**-0.1897**	<0.0001***	**-0.2857**	<0.0001***

4. Conclusions

Residential mortgage loans have several statistical characteristics of highly-skewed distribution and non-negative integer values of the dependent variable. So the frequency and phenomenon of data that using Poisson loglinear model method are more suitable than the original module.

For the data of residential mortgage loans, this positive value of skewness indicates a pile-up of scores on the left of the distribution, its shape look like Poisson distribution. So we need to examine whether a distribution of scores is normal or not. Testing the Kolmogorov-smirnov one-sample test, the results indicate that the data came from a population with the Poisson distribution. For other Tables, we can find that a deviation from normal, uniform, and exponential distribution respectively. For detecting multicollinearity, we find the tolerance has the values that are all more than 0.85, and the variance inflation factor (VIF) has the values that are all less than 1.5. Therefore, no multicollinearity is evident.

Finally this study compared Poisson loglinear model and ordinary linear regression model in a credit risk models to reduce the cost of incorrect determination. Although many researchers analyzed count data by ordinary linear regression, comparing above two previous regression analyses, all the estimate values of ordinary linear regression model are large Poisson loglinear model, but intercept is not significant and illegitimate. Therefore, we find that Poisson regression has the advantage of being precisely suitable for the discrete data of residential mortgage loans.

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An Empirical Investigation of Mediating Effect on Corporate Social Responsibility and Financial Performance: From Intangible Assets Perspective

Shen-Ho CHANG[1]
Feng-Yi HSU[2]
Hsiang-Ju CHEN[3]

[1]Associate Professor, Department of Accounting and , Centre for Environmental Accounting Research, Feng Chia University, Taiwan, R.O.C.
TEL:+886-4-24517250 ext.4231, E-Mail: shchang@fcu.edu.tw
[2]Ph.D. Program in Business, Feng Chia University, Taiwan, R.O.C.
TEL: +886-910005746, E-Mail: fengyi@mail.nmmst.gov.tw
[3]Associate Professor, Department of Business Administration, De-Lin Institute of Technology, Taiwan, R.O.C.
TEL: +886-2-22733567 ext.5108, E-Mail: hjc526@yahoo.com.tw

ABSTRACT

Corporate social responsibility (CSR) becomes a major issue in recent years and the correlation between CSR and corporate financial performance (CFP) is one of the research interests in related literature. However, the conclusion didn't reach consensus. This study gets ride of traditional statistical model and utilizes intangible assets as mediating variable instead to discuss whether the mediating effect can effectively promote both CSR and CFP.

Publicly traded companies to be awarded the Corporate Social Responsibility prize of Global Views Monthly and the Excellence in Corporate Social Responsibility prize of CommonWealth for the period spanning 2007-2011 were examined as samples in this study. Apart from the difference in evaluation indicators or questionnaire survey, companies which endeavor to fulfill social responsibility would contribute to promote corporate image and to increase intangible assets that providing long-term benefits.

Relationship between CSR and CFP was examined from the perspective of intangible assets. Results show that no significant influence of CSR on CFP, but CFP indeed significant influenced CSR and therefore increase its social responsibility. Further, the relationship between CSR and CFP can be improved by the mediating effect of intangible assets.

Keywords: *Corporate Social Responsibility, Tobin's_Q, Intangible Assets, Mediating Effect*

1. Introduction

Following the trend of environment protection, and the awakening of moral consciousness and consumer's self-awareness, the transition from pursuing profit maximization to creating social value, improving corporate image and in turn, integrating corporate social responsibility (CSR) into management philosophy resulted in the publicly traded companies to be awarded the Corporate Social Responsibility prize of Global Views Monthly and the Excellence in Corporate Social Responsibility prize of Common Wealth in Taiwan.

Although there is no universally accepted definition of CSR, an organization's commitment to operate ethically within social communities can be the common explanation. The concept of CSR was first introduced by Oliver Sheldon in 1923 and to be believed that enterprises do not only have the economic obligations and legalities, but also assume the social responsibility which beyond these obligations. According to Bowen (1953), CSR refers to the obligations of businessmen to pursue those policies, to make those decisions, or to follow those lines of action which are desirable in terms of the objectives and values of our society. While Levitt (1958) viewed CSR from direct opposition with the argue that doing welfare of the society is government's responsibility. Friedman (1970) believed that companies should focus on value creation plans and earn only profits for shareholders. Stakeholder theory (Freeman, 1984) argues that performance evaluation should not only by shareholders satisfaction, but also by providing other parties, including employees, customers, suppliers, financiers, communities, the maximum value satisfaction.

The majority of literature discussed the relationship between CRS and corporate financial performance (CFP), and there is an ongoing discussion of the relationship in empirical study. However, the relationship between CRS and CFP is still open to debate due to different methods used to analyze no consistent indicators.

Research suggested positive influence of CRS on CFP including Moskowitz (1972), Parket & Eilbirt (1975), Bowman & Haire (1975), Sturdivant & Ginter (1977), Cochran & Wood (1984), Waddock & Graves (1997), Preston & O' Bannon (1997), Ruf et al. (2001), Orlitzky et al. (2003), Tsoutsoura (2004), Allouche & Laroche (2005), Wu (2006), Kong & Zhang (2012), and Zhou (2012). On the contrary, authors possess the opinion that over-emphasize CRS would result in investing resources on activities other than shareholders profit maximization such as Hayek (1960), Friedman (1970), Bragdon & Marlin (1972), Davis (1973), Vance (1975), Aupperle et al. (1985), Brammer et al. (2005), and Shen & Chang (2008).

Further, some researchers investigate whether there's other variable exist to better explain the relationship between CRS and CFP. By considering the ability of stakeholders to reward or punish the firm base on their evaluations of the firm's activities, Peloza and Papania (2008) pointed out that it could change the relationship and a consistent relationship between CRS and CFP should not be expected. Surroca et al. (2010) examined the effects of a firm's intangible resources in mediating the relationship between corporate responsibility and financial performance and concluded an indirect relationship between CRS and CFP.

This study also examines the relationship between CRS and CFP, and the mediating effect of intangible assets. Publicly traded companies to be awarded the Corporate Social Responsibility prize of Global Views Monthly and the Excellence in Corporate Social Responsibility prize of Common Wealth for the period spanning 2007-2011 in Taiwan are example. In regard to the financial performance measurement indicator, return on assets (ROA) is adopted for the advantage of direct comparison with findings of other literature. Since Tobin's_Q is the ratio between market value and replacement value of the same physical asset, it is the measurement variable of intangible assets in following analysis.

2. Methodology

2.1 Sample and data resource

Financial data for those rewarding sample companies is collected from Taiwan Economic Journal (TEJ) Databank. Number of original sample data is dramatically dropped from 7,340 to 6,084 after deleting missing values. Final number of data used is 4,684 through further matching as shown in Table 1.

Table 1 Sample selection during 2007-2011 (firm-year lever)

Procedure	2007	2008	2009	2010	2011	合計
Number of original sample data	1,468	1,468	1,468	1,468	1,468	7,340
Number of sample data after deletion	1,125	1,167	1,233	1,256	1,303	6,084
Number of sample data through matching	-	1,094	1,155	1,209	1,226	4,684

2.2 Operational definition of variables

Corporate social responsibility status

Judges from whether to be awarded or not by the above-mentioned two magazines in Taiwan, sample companies are defined to be 1 for being awarded and 0 for not being awarded.

Corporate financial performance

As mentioned above, ROA percentage shows how profitable a company's total assets are in generating revenue. It's a useful variable to compare competing companies in the same industry and the top management capability. The formula to calculate ROA can be expressed as follow:

ROA = [Net income + Interest expense × (1- Tax rate)] / Average total assets

Intangible assets measurement

Q ratio which proposed first by Tobin (1950) is adopted here to measure intangible assets. Tobin's_Q is calculated by dividing the market value of a company by the replacement value of the book equity, and it encourages companies to invest more in capital when the value is greater than 1.

Chung and Pruitt (1994) suggested Approximate Q as the substituting formula and empirical study showed that with this new method, 96.6% variation of Tobin's-Q can be explained. Definition form of Approximate Tobin's_Q can be expressed as follow:

Approximate Q = (MVE＋PS＋DEBT) / TA

where

MVE: The product of a firm's share price and the number of common stock shares outstanding

PS：The liquidating value of the firm's outstanding preferred stock

DEBT: The value of the firm's short-term liabilities net of its short-term assets, plus the book value of the firm's long-term debt

TA: The book value of the total assets of the firm

Control variable

Since the management and development of intangible assets is bounded by tangible resources, this study also considers control variables such as physical asset, leverage, financial resource, scale, and risk. It is worth noting that, number of employees which put into the logarithm is treated as the indicator of company scale, and Beta coefficient is used to measure risk of company.

2.3 Construction of Regression Model

According to Baron and Kenny (1986), a three-step approach was proposed in which several regression analyses are conducted and significance of the coefficients is examined at each step. The step by step procedure is (1) conducting a simple regression analysis with independent variable (X) predicting mediator (M) (2) conducting a simple regression analysis with mediator (M) predicting dependent variable (Y) and (3) conducting a multiple regression analysis with independent variable (X) and mediator (M) predicting dependent variable (Y). Assuming there are significant relationships in Steps 1 and 2, one proceeds to Step 3. In the Step 3 model, some form of mediation is supported if the effect of mediator remains significant after controlling for independent variable. If independent variable is no longer significant when mediator is controlled, the finding supports full mediation. If independent variable is still significant, the finding supports partial mediation. This study follows model proposed by Surroca et al. (2010) to construct seven regression models as follows.

Model 1 explains the relationship among intangible assets, CSR, CFP, tangible resources and control variables and can be expressed like

$$\textbf{\textit{Tobin's Q}}_{it} = \alpha_0^{1} + \beta_1^{1} CSR_{it} + \beta_2^{1}\, CFP_{it} + \beta_3^{1}\, Physical\ resources_{it} + \beta_4^{1}\, Leverage_{it} + \beta_5^{1}\, Financial\ resources_{it} + \beta_6^{1}\, Size_{it} + \beta_6^{1}\, Risk_{it} + \varepsilon_{it} \ldots\ldots Model1$$

Model 2A evaluates the influence of independent variables, CSR in t-1 period, tangible resources and control variables, on CFP. Formula can be written as

$$CFP_{it} = \alpha_0^{2A} + \beta_1^{2A}\, CSR_{it-1} + \beta_2^{2A}\, Physical\ resources_{it} + \beta_3^{2A}\, Leveragei_{t} + \beta_4^{2A}\, Financial\ resources_{it} + \beta_5^{2A}\, Size_{it} + \beta_6^{2A}\, Risk_{it} + \varepsilon_{it} \ldots\ldots Model2A$$

Adding intangible assets to the preceding regression model 2A gives the Model 3A to evaluate the influence of CSR on CFP.

$$CFP_{it} = \alpha_0^{3A} + \beta_1^{3A}\, CSR_{it-1} + \beta_2^{3A}\, Tobin's\_Q_{it} + \beta_3^{3A}\, Physical\ resources_{it} + \beta_4^{3A}\, Leveragei_{t} + \beta_5^{3A}\, Financial\ resources_{it} + \beta_6^{3A}\, Size_{it} + \beta_7^{3A}\, Risk_{it} + \varepsilon_{it} \ldots\ldots Model3A$$

For these above models, when intangible assets do influence the causal relationship, regression coefficients should be turn out to be β11greater than 0 in model 1, β12A greater than 0 in model 2A, and when β23A greater than 0, β13A equals to 0 in model3A. To evaluate the influence of CFP in t-1 period, tangible resources and control variables on CSR, we obtain the model 2B:

$$CSR_{it} = \alpha_0^{2B} + \beta_1^{2B}\, CFP_{it-1} + \beta_2^{2B}\, Physical\ resources_{it} + \beta_3^{2B}\, Leverage_{it} + \beta_4^{2B}\, Financial\ resources_{it} + \beta_5^{2B}\, Size_{it} + \beta_6^{2B}\, Risk_{it} + \varepsilon_{it} \ldots\ldots Model2B$$

Adding intangible assets to the model 2B gives the Model 3B to evaluate the causal relationship between CSR on CFP:

$$CSR_{it} = \alpha_0^{3B} + \beta_1^{3B}\, CFP_{it-1} + \beta_2^{3B}\, \textbf{Tobin's\_ Q}_{it} + \beta_3^{3B}\, Physical\ resources_{it} +$$

$$\beta_4^{3B}\, Leverage_{it} + \beta_5^{3B}\, Financial\ resources_{it} + \beta_6^{3B}\, Size_{it} +$$

$$\beta_7^{3B}\, Risk_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Model3B$$

By the same token, when intangible assets act like a mediator, coefficients in model 2B and model 3B should be turn out to be β21 greater than 0, β12B greater than 0, and when β23B greater than 0, β13B equals to 0.

However, Surroca et al. (2010) pointed out that when relationship already exists among major independent variables and mediator, overestimating major independent variables and underestimating mediator would be an issue to be emphasized. Substituting major independent variable in model 3A and model 3B with the unexplained CFP residual and CSR residual, model 3A* and model 3B* can be expressed as:

$$CFP_{it} = \alpha_0^{3A} + \beta_1^{3A}\, CSR_{Residual} + \beta_2^{3A}\, \textbf{Tobin's\_ Q}_{it} + \beta_3^{3A}\, Physical\ resources_{it} +$$

$$\beta_4^{3A}\, Leverage_{it} + \beta_5^{3A}\, Financial\ resources_{it} + \beta_6^{3A}\, Size_{it} +$$

$$\beta_7^{3A}\, Risk_{it} + \varepsilon_{it-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Model3A^*$$

$$CSR_{it} = \alpha_0^{3B} + \beta_1^{3B}\, CFP_{Residual} + \beta_2^{3B}\, \textbf{Tobin's Q}_{it} + \beta_3^{3B}\, Physical\ resources_{it} +$$

$$\beta_4^{3B}\, Leverage_{it} + \beta_5^{3B}\, Financial\ resources_{it} + \beta_6^{3B}\, Size_{it} +$$

$$\beta_7^{3B}{}_{Riskit} + \varepsilon_{it-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Model3B^*$$

2.4 Empirical hypotheses

Hypotheses to be tested according to literature review and research objective are

Hypothesis 1. Intangible assets development is positively influenced by CSR

Hypothesis 2. Intangible assets development is positively influenced by CFP

Hypothesis 3. CFP is not significantly influenced by CSR but is significantly influenced by intangible assets due to the mediating effect of it

Hypothesis 4. CSR is not significantly influenced by CFP but is significantly influenced by intangible assets due to the mediating effect of it

2.5 Research framework

All the four hypotheses to be tested can be organized in Figure 1.

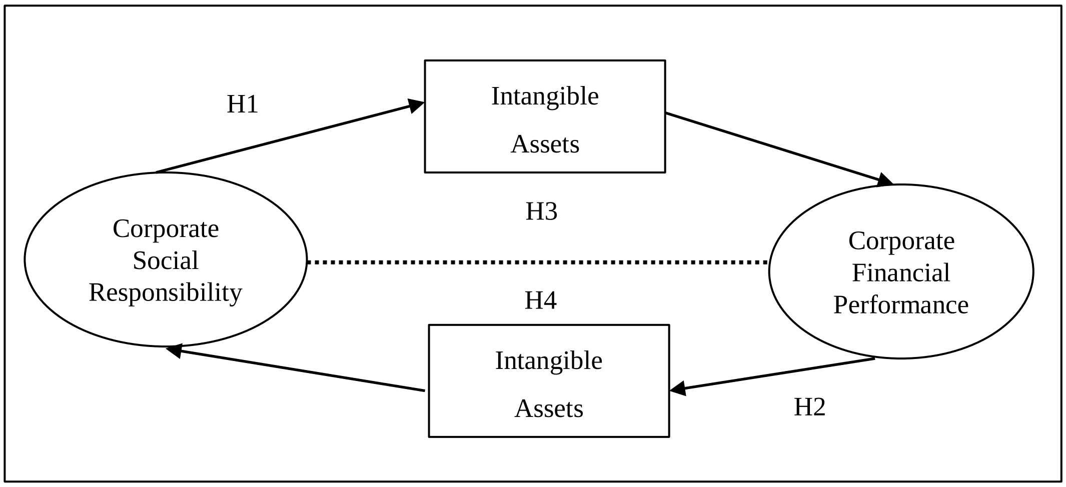

Figure 1 Research framework

3. Results

3.1 Influence of CSR and CFP on intangible assets

Empirical result for model 1 gives

$$\textbf{\textit{Tobin's\_ Q}}_{it} = 0.392 + 0.207CSR_{it} + 0.023\ CFP_{it} + 0.690\ Physical\ resources_{it}$$
$$-0.006\ Leverage_{it} + 0.003\ Financial\ resources_{it} + 0.02\ Size_{it}$$
$$+0.13Risk_{it} + \varepsilon_{it}$$

As we can see, CSR and CFP both have significant positive influence on intangible assets due to β11 ＝0.207 (P=0.002) and β21＝0.023 (P=0.000). The conclusion about hypothesis 1 and 2 are supported encourages the following discussion of relationship between CSR and CFP. The empirical estimates and tests of coefficients of other six regression model are summarized in Table 2.

3.2 Intercorrelation between CSR and CFP

Judges from the empirical results of model 2A and model 2B, CFP does not significantly influenced by CSR (β12A＝1.048, P = 0.255), but CSR is significantly positive influenced by CFP (β12B＝0.001, P = 0.018). It means that CFP indeed aids in the practice of CSR. However, whether this positive influence is mediated by intangible assets would be the next analysis to work on.

Table 2 Regression results

Y / X	Corporate Financial Performance (CFP)			Corporate Social Responsibility (CSR)		
	Model 2A	Model 3A	Model 3A*	Model 2B	Model 3B	Model3B*
Performance						
CFP				0.001 **	0.000 *	0.000
				(.018)	(.061)	(.480)
CSR	1.048	0.084	0.618			
	(.255)	(.924)	(.480)			
Intangible						
Tobin's_Q		3.850 ***	3.851 ***		0.009 ***	0.01 ***
		(.000)	(.000)		(.002)	(.001)
Tangible						
Physical	-6.334 ***	-8.413 ***	-8.415 ***	0.014	0.009	0.007
Leverage	-0.552 ***	-0.479 ***	-0.479 ***	0.001	0.001	0.001
Financial	0.104 *	0.085	0.085	0.000	0.000	0.000
Controls						
Size	3.764 ***	3.421 ***	3.377 ***	0.081 ***	0.081 ***	0.082 ***
Risk	0.069	0.016	0.039	-0.042 ***	-0.042 ***	-0.041 ***
Constant	-1.803 **	-3.165 ***	-3.083 ***	-0.149 ***	-0.152 ***	-0.153 ***
R^2	0.078	0.161	0.161	0.103	0.105	0.104
Number	4684	4684	4684	4684	4684	4684

3.3 Mediating effect of intangible assets on causal relationship between CSR and CFP

Summarized from the statistical results for model 2A and model 3A from Table 2, although the coefficient of CSR is not significantly greater than 0 (β 12A = 1.048, P = 0.255), and β13A = 0.084 (P = 0.924) is not significantly greater than 0 either, the larger significance p-value partially supports hypothesis 3 and the mediating effect is existed.

Therefore, for publicly traded companies to be awarded the Corporate Social Responsibility prize in previous period, CFP is significantly influenced by intangible assets at present period based on the empirical finding from model 3A. Compared the coefficients and significance of CSR between model 2A and model 3A, intangible assets of awarded companies in previous period do have mediating effect.

By the same token, judges from the significance of regression coefficients, hypothesis 4 is partially supported for that causal relationship between CFP and CSR is partial mediated by intangible assets.

3.4 Regression analysis with CSR residual and CFP residual

To avoid overestimating major independent variables and underestimating mediator, major independent variables in model 3A and model 3B were substituted by unexplained CFP residual and CSR residual to come up with model 3A* and model 3B*.

The regression models can be estimated as:

$$CFP_{it} = -3.083+3.851\ Tobin's\_Q_{it} -8.415\ Physical\ resource_{it} -0.479\ Leverage$$
$$+0.085\ Financial\ resource_{it}+3.377\ Size_{it} +0.039\ Risk_{it}$$

$$CSR_{it} = -0.153+0.01\ Tobin's\_Q_{it} +0.007\ Physical\ resource_{it}+0.001\ Leverage_{it}$$
$$+0.000\ Financial\ resource_{it}+0.082Size_{it} -0.041\ Risk_{it}$$

And the formulas of Residual CFPit and Residual CSRit can be expressed as follows.

$$Residual\ CFP_{it} = CFP_{it} - 3.851\ Tobin's\_Q_{it}$$

$$Residual\ CSR_{it} = CSR_{it} - 0.01\ Tobin's\_Q_{it}$$

Since the empirical outcome of model 3A* and model 3B* is the same, hypothesis 3 is remain partially supported. Nevertheless, hypothesis 4 is supported based on the regression statistics and it is enough to tell the truth that fully mediating effect of intangible assets exists between CSR and CFP.

4. Conclusion

This study examines the mediating effect on the causal relationship between CSR and CFP by the financial data from those publicly traded companies in Taiwan. The finding shows that CFP can be positive influenced by CSR but not significant for those awarded companies. On the contrary, CSR is significantly influenced by CFP.

Although CFP cannot be improved by CSR, however, there's benign circulation between CSR and CFP through the mediating effect of intangible assets. With the indicator of Tobin's-Q to measure intangible assets, this study verifies the partial mediating effect of intangible assets on causal relationship between CSR and CFP. It means that the benign relationship between CSR and CFP mediated by intangible assets would motivate company to contribute to the practice of social responsibility.

Although sample companies don't cover the majority of publicly traded companies, the idea to propose new model for the line of research in this study is believed to be able to attract more attention on further research topics and direction.

5. Future Research

Since the data used in this study only accounts for 2% of the companies that awarded the Corporate Social Responsibility prize, to decrease bias of the result and therefore, to give robust conclusion, matching companies with those also awarded similar corporate sustainability prize and including them in the sample for further analysis is suggested.

Future study will not just modify statistical analysis method, but also pay more attention on elaborating management implementation of the conclusion.

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Impacts of Knowledge Leadership and the Characteristics of Organizational Structure on Employee Learning Motivation in the Cultural and Creative Industries

Yuan-Cheng CHANG[1]
Wen-Yu CHIU[2]
Yuan-Duen LEE[3]

[1]Ph D Candidate, Graduate Institute of Educational Entrepreneurship and Management, National University of Tainan (Taiwan);
E-Mail: chen11777@hotmail.com

[2]Ph D, Assistant Professor, Department of Recreation and Sports Management, Shu-Te University (Taiwan);
Address: No.59, Hengshan Rd., Yanchao Dist., Kaohsiung City, 82445 Taiwan, R.O.C.
TEL: +886-7-615-8000 ext. 6412 Corresponding author: christinechiu@stu.edu.tw

[3]Ph D, Professor, Graduate School of Business and Operations Management, Chang Jung Christian University, Taiwan.
E-Mail: ydlee@mail.cjcu.edu.tw

ABSTRACT

This study explores the influence of knowledge leadership and the characteristics of organizational structure on employee learning motivation in the cultural and creative industries in Taiwan. A questionnaire survey of related enterprises was conducted with stratified sampling, resulting in a collection of valid samples from 36 firms, with 76 copies completed by mid- and high-level managers and 309 by other employees. A hierarchical linear modeling (HLM) analysis of the data was carried out, and the results indicate that in terms of the characteristics of organizational structure, neither formalization nor centralization has a significant influence on employee learning motivation. The practice of knowledge management as an aspect of knowledge leadership has a significant, negative influence on employee learning motivation. In contrast, creating a learning environment has a significantly positive influence on employee learning motivation. In terms of knowledge leadership, knowledge sharing and evaluation have a negative moderating effect on the relationship between a centralized organization and employee learning motivation. Creating a learning environment has a positive moderating effect on the relationship between a formalized organization and employee learning motivation. The promotion of knowledge management has a negative moderating effect on the relationship between a centralized organization and employee learning motivation.

Keywords: *Knowledge Leadership, Characteristics of Organizational Structure, Learning Motivation*

1 Introduction

1.1 Research Background and Motivation

As the global economy has transitioned into a knowledge economy in the 21st century, traditional ways of thinking about and modeling economies are now being critically challenged. The Organization for Economic Cooperation and Development (OECD) has noted that knowledge is now the major driving force for economic development, and thus it is important for organizations to address the issue of learning and engage in knowledge management and innovation, as these can lead to improved performance (Drucker, 1995).

The cultural and creative industries are closely related to the knowledge economy, and are regarded as part of the fourth wave of economic power. The development of such industries has thus become a major goal of many governments around the world (Hsia, 2009). For example, in 2002, the cultural and creative industries were included in the Taiwanese government's economic development priority project, known as Challenge 2008: National Development Plan. In the context of this project, the cultural and creative industries include those enterprises that use creativity and culture as resources for their business operations and for the development and management of intellectual property rights. A 2006 survey of the cultural and creativity industries in Taiwan found that companies within this classification reported a total of US$19.6 billion in revenue, generated US $10.2 billion in added-value, and employed a total of 207,785 people, representing a growth in employment of 6.18% from 2005 (Council for Cultural Affairs, ROC, 2008). Indeed, Taiwan's cultural and creative industries grew each year from 2002 to 2006, indicating that it is a sector of the economy that deserves more attention, due to its growing importance.

However, effective organizational learning and knowledge innovation require not only appropriate management methods and skills, but also better leadership performance (Wu and Lin, 2004), and specifically an approach known as knowledge leadership (Chang, Fan and Chang, 2008). Knowledge leaders utilize knowledge to improve their professional expertise in order to establish a knowledge innovation system and learning environment within an organization, with the aim of improving employee work performance and overall organizational effectiveness (Cavaleri, Seivert and Lee, 2005). An organization's structure is a crucial factor that affects its operating systems and processes (Khatri and Budhwar, 2002), and certain characteristics can provide an enterprise with a high degree of flexibility and control, and thus raise its response capabilities and competitive efficiency (Wang & Tai, 2001). Kogut and Zander (1992) propose that organizational learning enables an organization to acquire new knowledge or integrate existing knowledge to make improvements and evolve to better meet the challenges of a changing environment. An enterprise can become a learning organization when all of its employees are committed to learning, and an organization that is able to continuously use knowledge and information to enhance the overall solidarity and attitude of its employees will be better able to achieve the goals of innovation and progress (Huang and Chang, 2008).

To date, most studies on the cultural and creative industries have focused on the issues of cultivating creativity, gatekeeper mechanisms, the influence of education and gender issues, and few have examined issues related to business operations and management (Yang and Wu, 2005). A review of existing studies suggests that leadership styles and the characteristics of organizational structures are two major factors that affect the learning motivation of organizational members (McDermott and Sarin, 2003), and if these are not appropriate for this context, then the resulting negative effects will increase the difficulties that an organization faces with regard to changes in its external environment. Therefore, this study examines the relationships among the knowledge leadership of mid- and high-level managers, the characteristics of organizational structure, and employee learning motivation in the context of the cultural and creative industries in Taiwan.

1.2 Research Purpose

As noted above, the primary purpose of this study is to investigate the relationships among knowledge leadership of mid- and high-level managers, the characteristics of organizational structure and employee learning motivation in the cultural and creative industries in Taiwan.

The specific goals of this study are as follows:

(1) Exploring the influence of knowledge leadership and organizational structure on employee learning motivation.

(2) Examining the moderating effects of knowledge leadership on the relationship between organizational structure and employee learning motivation.

(3) Providing suggestions with regard to future research and the practical implications of this work.

2 Literature Review

2.1 Relationships among Knowledge Leadership, Characteristics of Organizational Structure, and Learning Motivation

Skyrme (2000) proposes that knowledge leadership is more effective than knowledge management in the organizational development of information resources, individual skills and knowledge learning networks. Managerial leadership is one aspect of the organizational environment, and the relationship between managers and employees is an important factor in the ability of latter to innovate (Clapham, 2000). Successful leaders must be able to create a learning environment in order to better manage organizational knowledge (Hewlett, 2006) and encourage employees to continue learning, and thus managers should establish communication channels to facilitate learning (Nonaka and Konno, 1998). Accordingly, the leadership of knowledge leaders is essential in the promotion of organizational innovation. As indicated by the existing literature, knowledge leadership is generally believed to have certain impacts on employee learning motivation, and so this study presumes that **knowledge leadership has a significant, positive influence on employee learning motivation.**

Kim (1993) refers to organizational learning as a process of organizational evolution in which the organization works to acquire and improve the abilities to act more effectively (Heijden, 2004). Organizational learning can also lead to the cultivation of new potential for further development (Gomes, 2004), as well as be better able to adjust in the face of environmental changes (Lin, Huang and Tung, 2004). Accordingly, it can be argued that a proper integration of organizational structure and a learning culture can help in the development of a learning organization, and, due to its impact on the spread of cultural values, an inappropriate organizational structure (such as one based on decision-making authority centralization) is bound to affect the circulation of knowledge (Hargadon, 1998), potentially to the extent that the organizational purposes of knowledge innovation and application cannot be served (Grant, 1996). In order to meet the challenges of rapid changes to the external environment, an organization should maintain a structure that is highly flexible (Liebowitz and Beckman, 1998), and thus can also facilitate employee learning (Cegarra-Navarro and Rodrigo-Moya, 2007). Therefore, this study presumes that **the characteristics of organizational structure have a significant influence on employee learning motivation.**

According to Frohman (1998), an integrative organizational culture can integrate individual abilities and organizational goals to enable employees at all levels to innovate and establish appropriate organizational values, beliefs and working systems for the promotion of learning, knowledge innovation and sharing (Gold, Malhotra and Segar, 2001). Later studies suggest that forming a culture of learning promotion has become increasingly important for organizational development (Pangarkar and Kirkwood, 2002), and that organizations with an established culture of openness, joint participation, and the pursuit of efficiency and growth are inclined to achieve greater levels of innovation (Li, 2006). To aid in this process, organizational leaders can act to create a conducive learning environment for employees (Shalley and Gilson, 2004), in which a culture of open communication and learning promotion should be established (Lewis, 2000; Berson, Nemanich, Waldman, Galvin, Keller, 2006).It has also been found that the organizational structure of an enterprise tends to reflect the extent to which it welcomes both innovations and reforms, while a high level of centralization will make it more difficult for employees to absorb or transfer knowledge, and a low level will encourage a willingness to learn and innovate among employees, as well as greater loyalty (Sims, 1996). As most of the related studies show, leaders are an important factor with regard to employee learning, and organizational structure may affect employee learning motivation. Therefore, this study presumes that **knowledge leadership has a moderating effect in the relationship between the characteristics of organizational structure and employee learning motivation.**

3 Research Methods

3.1 Research Hypotheses and Framework

Based on the background to this study, the hypotheses examined in this work are as follows, with the conceptual framework shown in Figure 1:

H1: The characteristics of the organizational structure have a significant impact on employee learning motivation.

H1-1: Formalization has a significantly positive effect on employee learning motivation.

H1-2: Centralization has a significantly negative effect on employee learning motivation.

H2: Knowledge leadership has a significantly positive effect on employee learning motivation.

H3: Knowledge leadership has a significant moderating effect in the relationship between the characteristics of organizational structure and employee learning motivation.

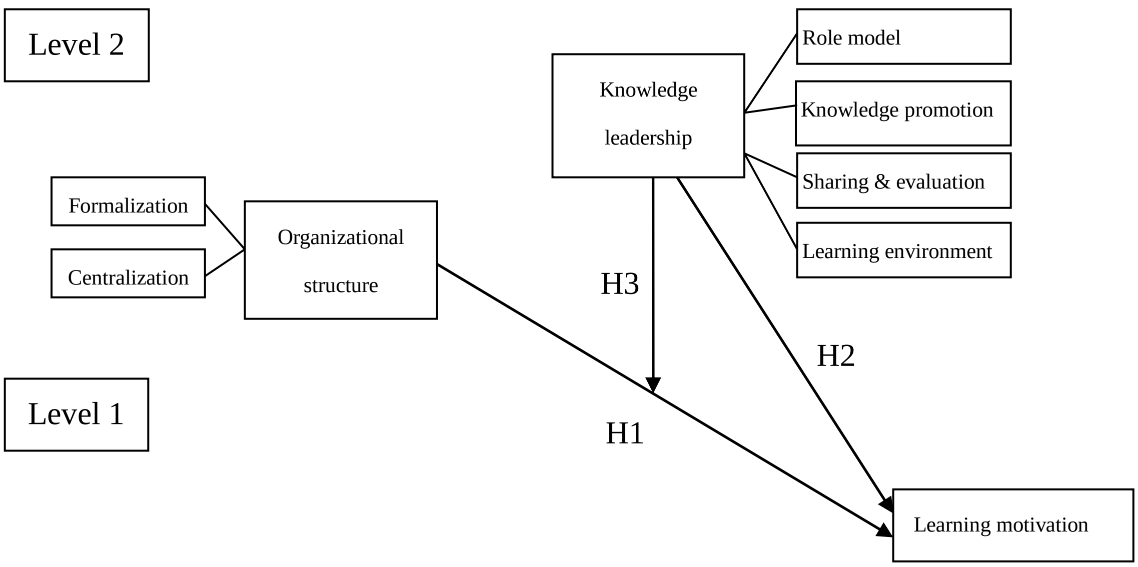

Figure 1 Conceptual Framework

3.2 Research Subjects

This study adopted two questionnaires to assess the opinions of high-ranking managers and other employees working for enterprises in the cultural and creative industries in Taiwan. The questionnaire for the managers contains items on the characteristics of organizational structure, while that for the employees contains items on knowledge leadership and employee learning motivation. The sampling methods used in this study were as follows:

This study employed a stratified purposeful sampling approach to select respondents from the cultural and creative industries in Taiwan. First, a sampling of enterprises was conducted. According to the Taiwan Cultural and Creative Industries Annual Report (Council for Cultural Affairs, Executive Yuan, 2008), there were a total of 12 categories of such enterprises in 2008. This study drew a number of samples from each category in proportion to the total number of enterprises, with a minimum of one sample from each. The sampling selected a total of 100 enterprises from the 12 categories: six from visual arts, three from music and performance, 20 from handicrafts, one from cultural exhibitions, one from movies, three from broadcasting and television, seven from publishing, 15 from architectural design, 25 from advertising, five from design, 13 from digital recreation and entertainment, and one from creative living.

The two questionnaires were distributed to mid- and high-level managers and the related employees in the three departments of human resources, marketing and production, and research and development. The managers answered questions on the characteristics of organizational structure, with a total of 300 copies of the survey being sent out, with one copy to each department. The employees answered questions on knowledge leadership and employee learning motivation, and a total of 1,500 copies of the survey were sent out, with five copies to each department. Valid responses were received from 36 firms, with 76 copies completed by the managers and 309 by employees. The response rates for the enterprises, managers and employees were thus 41%, 25% and 21%, respectively.

3.3 Research Variables and Measurement

3.3.1 Knowledge leadership

To measure knowledge leadership, this study modified the Knowledge Leadership of High Level Business Executive Scale proposed by Lee, Huang, Chang and Lu (2011), with reference to relevant scales developed by Viitala (2004) and Wu and Lai (2007) to compose a total of 28 questions in the four categories of role model, knowledge management promotion, knowledge sharing and evaluation, and creating a learning environment. A Confirmatory factor analysis using LISREL found that the factor loadings on knowledge leadership are between 0.71 and 0.94, all above the 0.05 significant level. SRMR=0.042. The values of GFI and AGFI are respectively 0.68 and 0.61. PGFI=0.57, indicating an acceptable fit of the theorized model to observed data. The values of NFI, NNFI and CFI are respectively 0.96, 0.96 and 0.97, all of which are greater than 0.90, CN=62.55, indicating good construct validity.

3.3.2 Characteristics of organizational structure

To measure characteristics of organizational structure, the study employed the organizational structure scale developed by Wang and Tai (2001) to design six questions in the two dimensions of centralization and formalization. The results of confirmatory factor analysis indicate: SRMR=0.068. The values of GFI and AGFI are 0.92 and 0.78, close to the standard value of 0.9. PGFI=0.35. These values represent an acceptable fit of the model to observed data. The values of NFI, NNFI and CFI are respectively 0.90, 0.82 and 0.91, close to the standard of 0.90, CN=67.69, indicating an acceptable construct validity.

3.3.3 Learning motivation

To measure learning motivation, this study referred to the scales developed by Boshier (1971), Huang (1996) and Chen and Chiu (2009) to draw up seven questions in the three dimensions of personal goal, learning orientation and environment factor for a scale pre-test. A purposive sampling was conducted amomg 150 employees from the cultural and creative industry, resulting in a collection of 133 vaild samples. An exploratory factor analysis of the samples indicates: KMO is 873 with cumulative variance explained at 63.913. Question No. 1 whose factor communality is less than 1.5 was eliminated. As a result of a second factor analysis, KMO is 888 with cumulative variance explained at 65.279. Following a reliability analysis, Cronbach's α is 0.916, indicating a high reliability. Finally six questions have been composed for learning motivation regarding pursuing progress, thought of lifetime learning, mutual learning partnership among employees, group growth experience, and various organizational supports for employees to engage in professional development.

A Confirmatory factor analysis using LISREL indicates: The factor loadings on learning motivation are between 0.71 and 0.94, all above the significant level of 0.05. Meanwhile, the values of measure indeics including SRMR=0.042, GFI=0.94, NNFI=0.95, CFI=0.97, RMSEA=0.14, and SRMR=0.031, have reached the standards recommended by Hair Jr. (1998). The Cronbach's α values of internal consistence coefficients are 0.678,0.766、0.891、0.839、0.854, indicating great reliability and validity of the construct.

4 Result Analysis

4.1 Data testing

The test of learning motivation as a dependent variable indicates that ICC1 (intraclass correlation 1) is 0.453 and ICC2 (intra-class correlation 2) is 0.816. According to the standards recommended by scholars (Bryk and Raudenbush, 1992), an indicator is suitable with ICC1 close to 0.12 and ICC2 close to 0.6., indicating a reasonable cross-level analysis. ICC1=0.453 indicates that there is 45.3% difference in learning motivation between enterprises. ICC2 indicates that its samle mean reliability is 0.816. Both ICC1 and ICC2 satisfy the standards for a cross-level analysis. Thus, this study employed HLM to conduct a cross-level analysis.

4.2 HLM Result Analysis

4.2.1 Null model

As the figures of a ststistical analysis show, between-group variance $\chi2=287.143$, df＝35, p＝0.00, between group component $\tau00=0.452$ meaning 45.2% between groups and reaching a significant level (p=0.00), the dependent variable has a significant within-group and between-group variability. It indicates that there are differences between enterorises in employee learning motivation, rejecting the null hypothesis. Therefore, the studty proceeded to perform a cross-level HLM analysis.

4.2.2 Cross-level analysis

The cross-level analysis was conducted in two steps. Firstly, the study used intercepts as outcome model to decide the predictability of organizational structure and knowledge management for organizational employee learning motivation. Subsequently, the study adopted slopes-as-outcomes model to explore whether knowledge leadership has a moderating effect on the relationship between organizational structure and employee learning motivation.

The model of HLM for the moderating effect of knowledge management on the relationshp between organizational structure and learning motivation is as follows:

Following the HLM analysis, the results of intercepts as outcome model, as shown in Table 1, indicate that both organizational formalization and centralization have no significant influence on employee learning motivation and that H1 is not supported. In the dimension of knowledge leadership, both knowledge promotion and learning environment have a significant impact on learning motivation （$\gamma02=-0.891$, p＝0.029, $\gamma04=0.429$, p＝0.017）. However, role model and sharing and evaluation have no influence on learning motivation. Knowledge promotion has a negative influence on employee learning motivation.

According to the results of slopes-as-outcomes model analysis, as shown in Table 1, the coefficients for the interactions between formalized organizations and the factors of sharing and evaluation and learning environment in the dimension of knowledge leadership have reached a significant level (γ09＝-0.487, p＝0.017, γ10＝0.380,p＝0.035). It indicates that the two factors have a moderating effect on the relationship between organizational formalization and organizational memberlearning motivation. The measure of knowledge sharing and evaluation taken by the leaders will lower the learning motivation of employees in a formalized organization (Figure 2). However, the creation of a good learning environment by the leaders in a formalized organization will enhance employee learning motivation (Figure 3).

Meanwhile, the coefficients for the interactions between organizational centralization and the factor of knowledge promotion in the dimension of knowledge leadership have reached a significant level (γ12＝-0.569，p＝0.016). It indicates that knowledge promotion has a moderating effect on the relationship between centralized organizations and organization employee learning motivation. Accordingly, the enforcement of knowledge promotion by the leaders will reduce the learning motivation of employees in a centralized organization (Figure 4).

Table 1

	Null model	**Random coefficient model**
Intercepts as outcome model		
γ00	5.254*	5.208*
Characteristics of organiationa structure		
Formalizationγ01		-0.002
Centralizationγ02		-0.190
Knowledge management		
Role modelγ03		0.977
Knowledge promotionγ04		-0.890*
Sharing and evaluationγ05		0.281
Learning environmentγ06		0.429*
Slopes as outcome model		
Formalization×Role modelγ07		0.841
Formalization×Knowledge promotionγ08		-0.795
Formalization×Sharing and evaluationγ09		-0.487*
Formalization×Learning environmentγ10		0.380*
Centralization×Role modelγ11		0.361
Centralization×Knowledge promotionγ12		-0.569*
Centralization×Sharing and evaluationγ13		0.370
Centralization×Learning environmentγ14		-0.145
Variance component		
INTRCPT1, U0	0.452*	0.037*
level-1, R	0.546	0.548

*p<.05

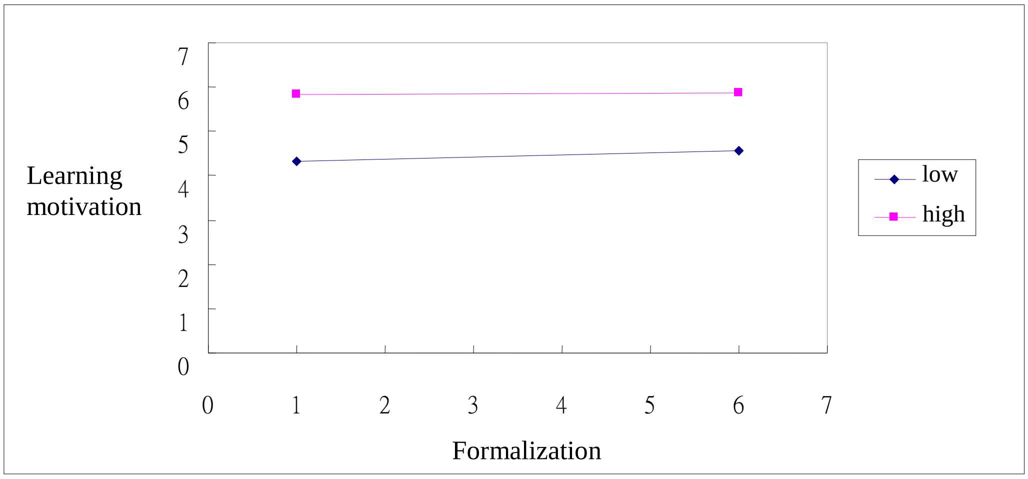

Figure 2 Interaction between organizational formalization and learning motivation in terms of knowledge sharing and evaluation

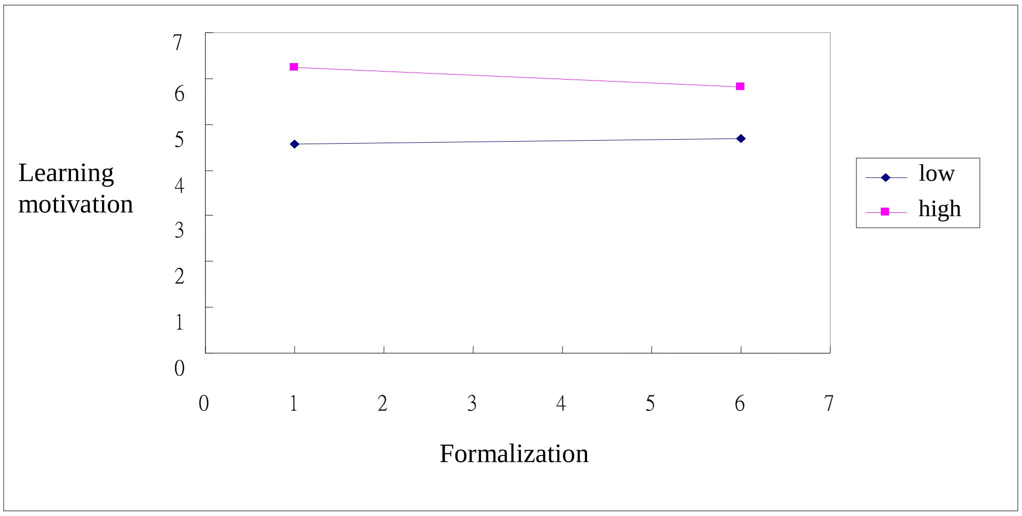

Figure 3 Interaction between organizational centralization and learning motivation in terms of learning environment and evaluation

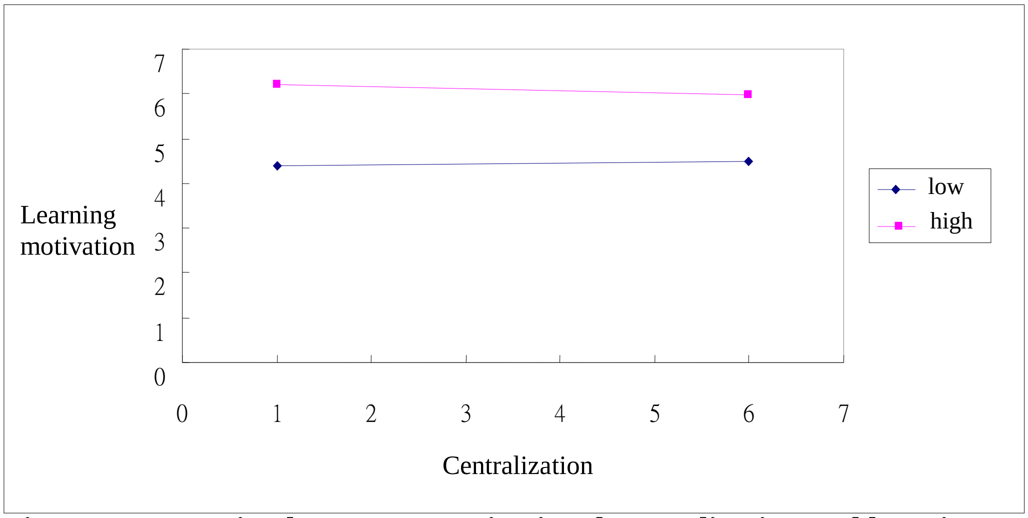

Figure 4 Interaction between organizational centralization and learning motivation in terms of knowledge promotion

5 Conclusions and Suggestions

This study aimed to determine the effects of knowledge leadership and organizational structure on organizational member learning motivation in the cultural and creative industry in Taiwan. The results are given as follows:

5.1 Influence of organizational structure and knowledge leadership on employee learning motivation

In the dimension of organizational structure, both formalization and centralization have no significant influence on employee learning motivation. This empirical result does not support the first research hypothesis. However, it should be noted that 63.4% of the enterprises, as indicated by the collected data, have been operating for less than three years. The degree of formalization or centralization for these firms remains unclear. That may explain the conclusion of this study that organizational structure has no influence on organizational member learning motivation.

In the dimension of knowledge leadership, knowledge promotion has a negative influence on organizational employee learning motivation, indicating that knowledge promotion will result in lower organizational employee learning motivation. It can be argued that in the process of knowledge promotion, the leaders will pay attention to resource integration, strategy development, the establishment of procedures and informational system and knowledge database construction, which will increase workload and learning pressure on employees.

5.2 Moderating effect of knowledge leadership in the relationship between organizational structure and organizational member learning motivation

The variable of knowledge sharing and evaluation in the dimension of knowledge leadership has a negative moderating effect on the relationship between formalized organizational structure and organizational member learning motivation. It indicates a formalized organization whose leaders place greater emphasis on knowledge sharing and evaluation will encounter a lower member learning motivation. In a formalized organization, the leaders who demand employees to share their work experience and establish evalution measures to ensure work effectiveness and individual contributions will increase work pressure on employees. Enterprises in the cultural and creative industry tend to encourage their employees to be individually creative. Their learning motivation will decrease when they are instructed by the leaders to share their creativity and experience.

Creating a learning environment has a positive moderating effect on the relationship between formalized organizational structure and organizational member learning motivation. In the creation of a learning environment, the leaders work to enhance infrastructural equipment and trust employees to perform at work within their capacity according to organization-designated procedures and regulations. Given a desirable working environment and a omprehensive organizational system, employees are able to perform their specialties and increase their learning motivation.

Knowledge management has a negative moderating effect on the relationship between centralized organizational structure and learning motivation. In a centralized organization, the leaders will exercise their power to order employees to follow their measures on organizational adjustment, resource integration, and knowledge and skill promotion for knowledge management. When employees are not voluntary to promote knowledge management, their learning motivation will be low.

The results of the study indicate that with most enterprises in the cultural and creative industries in Taiwan underdeveloped, organizational structure has no influence on learning motivation. However, knowledge leadership has a moderating effect on employee learning motivation. Accordingly, the leadership style is a key factor for organizational learning in developing enterprises in the cultural and creative industries.

Different from other industries, cultural and creative industries place more emphasis on the development of organizational and individual creativity. Further research may be conducted by comparing different industries to decicde the facors affecting employee learning motivation. With the cultural and creative industries in the initial stage of development in Taiwan, more research should be conducted to provide empirical results as a reference for government officials, businesses and academics to expedite the expansion of the newly emerging industries.

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Does Noise Matter on Hedging Effectiveness? Evidence from Taiwan

Juping WU[1]

Ren-Jean LIOU[2]

[1]Assistant Professor of Department of Finance, Shu-Te University, Taiwan, R.O.C.

[2]Associate Professor and Chairman of Department of Computers and Communications, National Pingtung Institute of Commerce, Taiwan,

TEL: +886-7-6158000-3212, E-Mail: juping@stu.edu.tw

ABSTRACT

This paper explores the relationship between different price components and optimal hedge ratios. The conventional estimation methods obtain optimal hedge ratios using original price series. In this paper, I propose associating original, pure-informed, and noisy added signals to estimate hedge ratios. Hedge effectiveness is obtained by incorporating most recommended methods, such as OLS, EC, and GARCH model. This paper proposes a wavelet approach to decompose the price series into informed and noise components and evaluate the hedging performance with the hedge ratios computed based on the two components. Using the Taiwan stock index and futures with three alternative models, the empirical results support the merit of this decomposition for the spot-futures hedge. The results show that, in a daily hedging strategy (i.e., short-term hedging), optimal hedge ratios are estimated using noise-added information. A de-noised signal better estimates long-term hedging effectiveness than does that of original information. Both low and high frequency portions of the signal are important for hedging purposes depending horizon. Noise is often in the form of market microstructure nature and serially correlated but no treatment is provided in the past researches. The practical implications for practitioners are considering that noise does affect hedging performance, particularly in the short run.

Keywords: *Hedging Strategy; Noise; Optimal Hedge Ratio; Emerging Market; Information Asymmetry*

1 Introduction

One of the best uses of derivative securities is hedging. Futures contracts are widely used as risk reduction tools in the spot market. Both academicians and practitioners have shown great interest in hedging with futures. The financial literature uses several approaches to determine optimal hedge strategies and to measure the effectiveness of these methods. One of the most widely used hedging strategies is based on minimized variance of the hedged portfolio (e.g., Johnson, 1960; Ederington, 1979; Myers & Thompson, 1989). In hedging studies, the most widely used models to estimate the optimal hedge ratios (OHR) are ordinary least squares (OLS), error-correction (EC), and generalized autoregressive conditional heteroscedasticity (GARCH) models. No consistent resolution exists in which an approach clearly dominates the alternatives.

The approaches for estimating the OHR assume that minimized risk depends on the price behavior difference between futures and spot prices. However, Copeland and Galai (1983) claimed that market price information contains an informed signal and a noisy signal, which dominate the fundamental trend (efficient price) and transitory price change. In information-based theories, Fama and French (1988) indicated that information asymmetry creates informed and noisy traders. Bagehot (1971) claimed that informed traders are the only traders who make prices move toward a fundamental trend. All other traders are noisy traders who add noise to price. Bandi and Russell (2005) argued that financial market prices are composed of permanent and transitory factors. Transitory factors are noises that lead to unanticipated price change, and permanent factors are informed signals that drive fundamental trend (e.g., Hansen & Scheinkman, 2009; Hansen et al., 2008). Therefore, according to market microstructure studies, market prices are composed of noisy and informed signals. Noise affects short-term market prices, but an informed signal influences long-term prices. Cecchetti et al. (1988) indicated that the return on a hedged position is normally exposed to risk caused by unanticipated changes in the relative price between the spot position being hedged and the futures contract. Hedging with futures markets may not eliminate risk completely because of the unpredictable price changes. Fama and French (1988) showed unpredictable price change to be the noise in information-based theories. Therefore, different noises affect the spot and futures market and further affect hedging effectiveness. On the other hand, due to the highly leveraged margin account and the more informed traders, a futures market is expected to have higher information asymmetry than spot market (Antoniou et al., 2005). The information asymmetry among futures and spot markets is expected to have different market behaviors and market price components, which may significantly causes the effectiveness of hedging strategies. Furthermore, Emerging markets1, as in Taiwan's equity market, have higher levels of asymmetric information than do developed markets.

[1] MSCI Inc., a global index provider, decided to maintain Taiwan's status as an emerging market in 2013.

However, the specific empirical analysis of optimal hedge ratios and different price components among futures and spot markets is still fairly scarce in literature. This article addresses different price components for estimating the hedge ratio and explores the relationship between price components and OHRs.

There is fairly few empirical studies related to our research focus on decomposing market price to informed signal and noise in literature. Fleming et al. (2000) and Capobianco (2003) argue that one of the key features of wavelet analysis is its ability to decompose non-stationary signals according to time and scale. Wavelet analysis allows us to decompose original price data into informed and noisy signal. In and Kim (2006) decompose data into low- and high-frequency contents with respect to various time scales. These frequencies can be respectively regarded as informed and noisy data. Wavelet analysis transforms a non-stationary signal into a higher dimension and preserves both frequency and time information. Wavelet analysis is capable of revealing data appearances, such as trends and discontinuities. Wavelet analysis achieves common data analyses, such as signal compression and de-noising, without evident degradation. Wavelet transform is an excellent tool for extracting the informed signal from the noisy observation.

Several recent applications have proposed using wavelet analysis in economics and finance. Hedging performance applications include examining the relationship between stock and futures markets as posited by Mallat (2008), estimating the hedge ratios for different hedging horizons by Lien and Shrestha (2007), and investigating the hedging effectiveness of the OLS hedging model in a dynamic moving-window by Conlon and Cotter (2012). Most of these methods involve applying wavelet analysis by using low-frequency components to estimate the multi-scale hedge ratio, which varies with the wavelet scales. Results have shown improved performance of the wavelet hedge ratio with an increased length of the hedging horizon. However, the hedging horizon is limited to the power of 2. For instance, if level 4 decomposition is used, the hedging horizon must be 16, which is impractical for daily use. This paper uses the dynamic minimum variance hedge ratio, which changes with the time. Our purpose is to not only examine the horizon-varying hedge ratio, but also to investigate the time-varying hedge ratio.

Using the wavelet technique, the optimal hedge ratios on time-varying are estimated by considering the informed and noisy components. This paper uses original, informed, and noisy signals to estimate the minimum variance hedge ratio conditionally by the bivariate GARCH model, and unconditionally by the OLS and EC models. The paper finds that, in a daily dynamic hedging strategy, optimal hedge ratios should be estimated by noise-added information. However, for long-term hedging purposes, hedging effectiveness estimated by the de-noised signal is better than those by the original information. Noise affects the covariance between the spot and futures market, particularly in the short run. In the long-term, the shared permanent component ties the stock and futures series together, and the effect of the noisy components becomes negligible. Therefore, the hedging strategy should consider the price components, noisy and informed signal, to enhance hedging performance effectiveness.

This paper is organized as follows. Section 2 presents the methodology used to estimate the optimal hedge ratios and the hedging effectiveness measurement. I also explain the wavelet decomposition technique. Section 3 presents a discussion on the data and empirical results. The paper ends by offering a conclusion.

2 Methodology

2.1 Wavelet Analysis

Financial time series data sets are perturbed by noise. Using informed and noisy signals separately to estimate hedge ratios should improve the hedge effectiveness on hedging strategy in financial markets. Wavelets are relatively new signal processing techniques in economics and finance (e.g., Mallat, 2008; Lien & Shrestha, 2007; Percival & Walden, 2000). In this section, I introduce the fundamental methods of wavelet analysis. More specifically, I describe the discrete wavelet transform (DWT).

Fourier analysis is one of the origins of wavelet analysis. The two methods allow going back and forward between the raw and transformed signals. However, wavelet analysis has three distinctive advantages over Fourier analysis (see In, 2012). First of all, wavelet analysis has the ability to decompose the data into several time scales instead of the frequency domain. Secondly, wavelet transforms allow us to have both very short and long basis functions. Thirdly, wavelet transforms have the ability to handle the non-stationary data. Since most financial data are non-stationary. Their transitory characteristics do not appear after Fourier transform, where time information is lost in the frequency domain. Unlike Fourier analysis, wavelet analysis preserves both frequency and time information. Therefore, I use wavelet analysis for extracting the noisy signal and informed signal from the whole price information.

Wavelet analysis decomposes a signal into shifted and scaled versions of the original wavelet. Continuous wavelet transform (CWT) constructs a time-frequency representation in a continuous manner. Let the original signal be x (t); the continuous wavelet transform at scale a and translation b is then expressed by

$$X(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-b}{a}\right) \tag{1}$$

where ψ(t) is the wavelet function.

CWT is a convolution of the input signal with the wavelet function. Numerous continuous wavelet functions have been invented for various applications (Figlewski, 1984). For practicality, I chose differentiable functions that are absolutely and square integrable to ensure the conditions of zero mean and square norm one, as follows:

$$\int_{-\infty}^{\infty}\psi(t)dt = 0$$

$$\int_{-\infty}^{\infty}\psi^2(t)dt = 1$$

Calculating CWT using all the wavelet coefficients is computationally impossible. If I choose scales and positions based on powers of two, that is, dyadic scales and positions, then the computation becomes more efficient while maintaining a similar accuracy. Furthermore, in time series analysis, the data has a finite length of duration. Only a finite range of scales and shifts are meaningful. Hence, I propose the discrete wavelet transform (DWT).

For many signals, the most significant information is found in the low-frequency region. The high-frequency content contains subtle variation and noise. In DWT, I categorize the wavelet coefficients into approximations and details. The approximations are the high-scale, low-frequency components of the signal named cA. The low-frequency characteristic is similar to fundamental trend. The cA is to be the proxy of the informal signal. The details are the low-scale, high-frequency components named cD. The high-frequency components are the similar to transitory price change. The original signal passes two complementary filters and emerges as two signals. The decomposition process can be repeated on successive approximations, which generates a tree-structured filter bank shown in Figure 1. The decomposition proceeds until the details consist of a single sample or a proper criterion is satisfied (see In, 2012).

[Figure 1 here]

In the wavelet decomposition tree, as in Figure1, the time series x(t) is filtered using the wavelet filter and scaling filter down-sampled by 2. The hedging horizon is limited to the power of 2. This paper uses the dynamic minimum variance hedge ratio, which changes with the time. Therefore, the hedging horizon could be unlimited but lower than 2λdecomposition. For instance, if hedging days are 5, the level (λ) is 3 to be used for decomposition.

In level λ decomposition, the coefficient of cD1, cD2,… to cDλmeans the proxy of excluding the degree of noisy information. The cAλ becomes the proxy of the degree of noisy information and informed signal. For instance, in level 1 decomposition, cD1=1 means excluding all noisy information. The cA1 equals to the original signals x(t). If cD1=1.1, the cA1 means combining informed signal and 110% noisy signal. In this article, I estimate the hedge ratios separately by original price, pure informed signal, and pure informed signal with different degrees of noisy signal. We could compare the hedging effectiveness with considering different degrees of noisy information.

2.2 Minimum Variance hedge and hedging effectiveness

The most widely used hedge ratio is the minimum variance (MV) on portfolio risk (e.g., Johnson, 1960; Enderington, 1979; Myers & Thompson, 1989), where risk is given by variance changes in hedge portfolio values. Since risk is usually measured as the volatility of portfolio returns, an intuitively plausible strategy might be to choose the hedge ratio that minimizes the variance of the returns of a portfolio containing the stock and futures position. This is known as the optimal hedge ratio (Brooks et al., 2002). Specifically, the return series are computed via the first difference of log-transformed prices – that is, Rt = log(Pt)-log(Pt-1)，The price P can be substitute separately by original price, pure informed signal, and informed signal with different degrees of noisy signal. Let RSi,t and RFi,t denote the daily continuous return on different degrees of noisy information i in spot and futures prices at time t, respectively. The optimal hedge ratio HRi,t is given by

$$HR_{i,t} = \frac{Cov(RS_{i,t}, RF_{i,t})}{Var(RF_{i,t})} \quad (2)$$

where Cov (RSi,t, RFi,t) is the covariance between the noise-adjusted spot and futures returns, and Var (RFi,t) is the variance of noise-adjusted futures returns. The time variation of the variance-covariance matrix is a well-known feature of many financial asset returns, leading to an optimal time-dependent hedge ratio, HRi,t.

The degree of hedging effectiveness, proposed by Ederington (1979), is measured by the percentage reduction in the variance between returns of un-hedged portfolios RSi,t and hedged portfolios RPi,t. Therefore, the degree of hedging effectiveness HEi can be expressed as follows:

$$HE_i = \frac{Var(RS_{i,t}) - Var(RP_{i,t})}{Var(RS_{i,t})} \quad (3)$$

The higher HEi means a higher risk reduction after the hedging strategy.

2.3 Estimating hedge ratios

In hedging studies, the most widely used models to estimate the optimal hedge ratios are OLS, EC, and GARCH models. No consistent resolution exists in which an approach clearly dominates the alternatives. The first approach regresses the spot return on the futures return using the OLS model, and the slope coefficient gives the estimated optimal hedge ratio (OHR; e.g., Enderington, 1979; Hill & Schneeweis, 1982; Sener, 1998). A second approach is based on EC model to estimate the OHR, which considers a set of economic variables in a long-run equilibrium (e.g., Engle & Granger, 1987; Ghosh, 1993; Lien, 1996). Given the time-varying nature of the covariance in many financial markets, a third approach adopts GARCH model to estimate time-varying OHRs (e.g., Kroner & Sultan, 1993; Park & Switzer, 1995; Choudhry, 2003; Wang & Low, 2003). Extensive debate has been conducted on which model generates the best hedging performance (e.g., Park & Switzer, 1995; Harris & Shen, 2003; Lien & Tse, 2002; Yang & Allen, 2004).

After decomposing the price information using wavelet transform, I use three models, OLS, EC, and GARCH, to estimate the optimal hedge ratios. The price information including the original signal, informed signal, and noise are considered individually. Hedge effectiveness is then compared among these models with different noise-adjusted prices to determine the best performance.

Conventional approaches for estimating the MV hedge ratio involve using the OLS regression technique to estimate the regression of spot returns on futures returns (Percival & Walden, 2000). To account for this time variation in the variance-covariance matrix, a rolling window OLS approach is used with all observations given an equal weighting. Specifically, the regression equation can be written as

$$RS_{i,t} = \alpha_i + \beta_i \cdot RF_{i,t} + \varepsilon_{i,t} \quad (4)$$

The HRi is given by the estimate of βi by regressing the noise-adjusted stock daily returns on the noise-adjusted futures daily returns. However, the rate of return is calculated by the difference equation, which expresses the variable value as a function of its own lagged values. Engle and Granger (1987) introduced the co-integration concept by considering a set of economic variables in a long-run equilibrium. Because the OLS model incorporates the long-run equilibrium between the spot and futures into the model, I use EC to estimate the following hedge ratio

$$RS_{i,t} = \alpha_i + \beta_i \cdot RF_{i,t} + \delta(LnS_{i,t-1} - \gamma LnF_{i,t-1}) - \varepsilon_{i,t} \quad (5)$$

where Si is the noise-adjusted stock price and Fi is noise-adjusted futures price. RSt and RFt denote the daily continuous return at time t, respectively.

I then use the bivariate GARCH. Because the OLS-based hedge ratio is obtained from a linear regression model, it is assumed to remain constant through time. However, time-varying volatility may exist. Therefore, I present the bivariate GARCH diagonal BEKK (Baba, Engle, Kraft, & Kroner) model by Engle and Kroner (1995) to be our dynamic hedging strategy. The model ensures a positive semi-definite, conditional variance-covariance matrix in the optimization process, which is a necessary condition for the estimated variance to be zero or positive. The GARCH model allows the conditional variance and covariance of the spot and futures prices to influence each other, and does not require estimating numerous parameters to employ. The bivariate GARCH (1, 1) model is expressed as follows.

$$RS_{i,t} = C_{i,s} + \varepsilon_{i,s,t}$$

$$RF_{i,t} = C_{i,f} + \varepsilon_{i,f,t}$$

Where $$\begin{bmatrix}\varepsilon_{ist}\\ \varepsilon_{ift}\end{bmatrix} \mid I_{i,t-1} \backsim N(0, H_{i,t}) \tag{6}$$

$$H_{i,t} = \begin{bmatrix} h_{i,ss,t} & h_{i,sf,t} \\ h_{i,sf,t} & h_{i,ff,t} \end{bmatrix} = C_0^{'}C_0 + A_{11}^{'}\varepsilon_{i,t-1}\varepsilon_{i,t-1}^{'}A_{11} + G_{11}^{'}H_{i,t-1}G_{11}$$

$$= \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}^{'} \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^{'} \begin{bmatrix} \varepsilon_{i,s,t-1}^2 & \varepsilon_{i,s,t-1}\varepsilon_{i,f,t-1} \\ \varepsilon_{i,f,t-1}\varepsilon_{s,t-1} & \varepsilon_{i,f,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}^{'} \begin{bmatrix} h_{i,ss,t-1} & h_{i,sf,t-1} \\ h_{i,sf,t-1} & h_{i,ff,t-1} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$

The return for noise-adjusted spot and futures series i are given by $RS_{i,t}$ and $RF_{i,t}$, the residual vector $[\varepsilon_{i,st}, \varepsilon_{i,ft}]$ is bivariate and conditionally normally distributed, and the conditional covariance matrix is represented by $H_{i,t}$. $h_{i,ss,t}, h_{i,ff,t}, h_{i,sf,t}$ are the conditional variance and co-variance of the errors $(\varepsilon_{i,st}, \varepsilon_{i,ft})$ from the mean equations. It -1 is the information set representing an array of information available at time t-1. The conditional MV hedge ratio at time t is given by $H_{i,t} = h_{i,sf,t-1}/h_{i,ff,t-1}$. This model allows the hedge ratio to change over time, resulting in a series of hedge ratios instead of a single hedge ratio for the entire hedging period.

3 Empirical Analysis

3.1 Description of the Market and Data

I use daily observations of Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and TAIEX futures contracts. The TAIEX is the most widely quoted of all Taiwan Stock Exchange (TWSE) indices2. Taiwan Futures Exchange (TAIFEX) opened for business and launched its first product, TAIEX Futures, on July 21, 1998. Therefore, our sample selection starts from January 1999 through December 2010 for twelve years. The data used in this paper were obtained from the Taiwan Economic Journal Database (TEJ). To avoid thin markets and expiration effects as in Huang (2004), I roll over to the next nearest contract when it emerges as the most active contract. The total number of observations is 3,021.

This paper uses the dynamic minimum variance hedge ratio, which changes with the time. Our purpose is to investigate the time-varying hedge ratio and daily dynamic hedge ratios are used. Therefore, firstly in level 1 decomposition by wavelet analysis, cD1=0, including all noisy information, means that the cA1 equals to the pure informed signals. Let S and F denote the original daily stock index and futures price, respectively. SW and FW denote the pure informed price on spot and futures. RS, RF, RSW, and

[2] TAIEX covers all of the listed stocks excluding preferred stocks, full-delivery stocks and newly listed stocks, which are listed for less than one calendar month.

RFW denote the daily continuous return and pure informed return on spot and futures, respectively. For the data characteristics, Table I provides a statistical summary of the original data and the pure informed signal.

[Table I here]

In Table I, the price and return series are all positive in the sample period. The lowest standard deviations are found in the SW (1,421) and RSW (1.43%) cases. Using wavelet analysis to eliminate the noise and retain the informed signal is reasonable to make standard deviations lower. For the unit root test, the price series are all non-stationary according to ADF (Augmented Dickey Fuller) statistics. However, stock and futures returns, defined as the first difference in the logarithm of daily closing prices, lead to stationary. Therefore, I use the return series to estimate the hedge ratio. The Johansen trace statistics show that the spot and futures prices are co-integrated, and that the error correction terms should be considered in the model specification. Finally, Q2 (24)[3] for the ARCH effects presents strong autocorrelations in the squared returns for all assets. Thus, I use the GARCH model for considering heteroskedacity.

3.2 The Empirical and Comparison Results

Investors must predict the future in the real world; therefore, it is necessary to determine whether the proposed model works well in out-of-sample hedging performance. I adopt the moving window estimation method that involves rolling over a particular number of samples to determine the series of out-of-sample rolling hedge ratios as shown in Figure 2. Specifically, for the total period T, I take J day observations from the sample and use these observations to estimate hedge ratios with all three hedging models for the next K hedge days. The one day hedge means K=1. The calculation is repeated for the following period, using the nearest available J day observations to estimate the hedge ratios. By continually updating the model estimation to the end of the data set, I complete T-J-K+1 forecasted hedge ratios for each model. I conduct the analysis using the different observations (rolling windows) to allow for behavior changes and exposure to different markets over time.

[Figure 2 here]

This paper uses the dynamic minimum variance hedge ratio, which changes with the time, to test the hedging horizon form one to sixteen days. The hedging horizon should be unlimited but lower than 2λ decomposition. For instance, if hedging days are 5, the level (λ) is 3 to be used for decomposition. Therefore, I perform wavelet analysis with one to four levels according hedge horizon. The different degrees of noise with informed signal are used to estimate the OHRs on three models. Table II presents the average hedge ratios of three models for a one-hedge day in one-level decomposition by wavelet analysis associated with each observation, J days, considered.

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3 $Q^2(24)$ is the Ljung-Box statistics for serial correlations in the squared series.

[Table II here]

As shown in Table II, this paper use six different observations to estimate the OHR. The average hedge ratios decrease as the observation day increases. When more noises are added in the return series, the hedge ratio decreases. In 90 observations, the hedge ratios on EC range from 88.938% to 84.449% for the pure-inform signal to 110% for the noisy signal. This implies that noise disturbs the correlation and hedge ratios between spot and futures markets. The more observation days also increase the noisy disturbances with decreased hedge ratios. In cD1=1, the hedge ratios form 83.014 to 81.698 for observations 60 days to 300 days in OLS method.

Comparing the three models, the hedge ratios are higher in EC than in OLS, except in the pure-informed signal. In 120 day observations, the 88.701% hedge ratio on OLS exceeds 88.657% on EC. In the original signal (i.e., 100% noise), the hedge ratio with the GARCH model is higher than that in OLS and EC models. In 180 observations, 85.662% on the GARCH model is higher than 84.092% on EC and 82.136% on OLS. The GARCH model adjusts error term heteroskedacity so that covariance between stock and futures market is higher than OLS and EC.

I compare the hedging performance of each model by considering the noisy signal. Table III presents the hedging effectiveness for the daily hedging strategy with different degrees of noise.

[Table III here]

In Table III, the effectiveness of EC exceeds OLS in almost all cases of different degrees of noise. In the original signal, the EC ratio is more likely to produce greater hedging effectiveness than OLS and GARCH models. In the original signal, the EC ratio is more likely to produce greater hedging effectiveness than OLS and GARCH models. Hedging effectiveness also increases as noise or observation day increases. In the daily-hedging strategy, the EC model is the most effective by adding 10% more noise to the original signal. The central argument of behavioral finance that mispricing the market price from the fundamental value exists and deepens in the short run has been proven. Noise-trader opinion causes higher market volatility for a relatively short horizon (Engle & Kroner 1995; Black, 1986). Therefore, in a daily hedge strategy, noise information affects covariance and should be added to estimate the hedge ratios for enhancing hedging performance.

Noise trading leads to a large divergence between market prices and fundamental value. In a longer hedging period, the hedge ratios relate more to the fundamental trend. Therefore, they should be estimated by focusing more on the informed signal than on the noise signal. In two hedge days, the hedge ratio estimated by de-noised information is more effective, as shown in Table IV.

[Table IV here]

Table IV shows thatcvfost effective hedge ratios are estimated on the EC model using 90% de-noised signals. These results differ from those obtained by Lien and Shrestha (2007), who estimated the hedge ratio by the pure-informed signal. I prove that the hedge ratios estimated by the pure-informed signal do not exceed those by the pure-informed signal adding 10% noise signal. Therefore, noise signals affect the covariance between spot and futures prices and count them for measuring optimal hedge ratios.

Tables V to VII show the summary of hedging effectiveness in different wavelet levels and periods. For matching the hedging horizon, I made the wavelet level scale slightly more than the hedging days. For instance, 5 hedge days are used for Level 3 because 23>5>22… I compare the hedging effectiveness for 3-16 hedge days. For brevity and practicality, I show the results for 5 (1 week), 10 (2 weeks), and 16 hedge days. The other results show the same tendency.

[Table V here]

[Table VI here]

[Table VII here]

Among Tables V to VII, I add noisy information to the lowest scales (highest frequencies). A small noise signal creates greater hedging effectiveness. Most optimal hedge ratios are estimated by the OLS model after 4 hedge days. The advantage of EC over OLS is considering the long-run equilibrium between spot and futures prices. The informed signal does not contain short-term noise, but long- term information. Therefore, the EC model only surpasses OLS in one or two hedge days. The EC may therefore not be the best model for long-term hedging.

Because GARCH model estimation uses time-varying volatility and error term, the hedge ratios must be evaluated with noise. Thus, I estimate the hedge ratio by the GARCH model only with the original signal. Because of the characteristics on time- varying volatility, the GARCH model is more suitable to estimate short-term hedge ratios. Therefore, our results show that the GARCH model does not outperform the OLS and EC, specifically in the long-term hedging strategy.

Our results are consistent with the findings obtained by Mallat (2008) and Lien and Shrestha (2007). Hedge-ratio performance by the pure-informed signal improves with increased length of the hedging horizon. Further exploration shows that hedge ratio estimation by a small noise signal prevails over the pure-informed signal or the original series, on both OLS and EC models. Therefore, noise affects hedging effectiveness and plays an important role in improving hedging performance. However, the hedging horizon is limited by 2 to the n powers in the study by Mallat (2008) and Lien and Shrestha (2007). This article releases that restriction. I estimate hedging days from 1 to 16, and enhance hedging-period flexibility.

4 Conclusion

Interested in new approaches on deriving optimal hedge ratios has grown rapidly in recent years as it plays an important risk reduction strategy in the spot market. The traditional approaches for estimating the optimal hedging ratios are estimated by using the original price behavior difference futures and spot prices. Microstructure models incorporate market price information by distinguishing between informed and noisy signals. This paper thus extends the optimal hedging strategy literature by developing a novel empirical measure of the noisy signals. Wavelet analysis allows us to decompose original data into informed and noisy signals. By applying wavelet decomposition, I improve hedging performances by considering noisy information. The informed signal induces a fundamental trend and drives the permanent factor. I use the original, informed, and noisy signal to estimate the minimum variance hedge ratio by the OLS, EC, and GARCH models and an out-of-sample rolling sample to estimate the hedge ratios. I find that, in a daily hedging strategy, optimal hedge ratios are estimated by noise-added information. In contrast, for long-term hedging, hedging effectiveness estimated by the de-noised signal is superior to the original information. Noise affects the covariance between the spot and futures market, particularly in the short run. Even in the long term, optimal hedge ratios are not estimated by the pure-informed signal, but with little noise. The results suggest that the practitioners should consider the noise on the hedging strategy, especially in the short term. The noise does affect the optimal hedging effectiveness. Furthermore, I release the limitation length of the hedging horizon and enhance the flexibility of the hedging period to a practical application.

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Table I. Basic Statistics

In level 1 decomposition by wavelet analysis, let cD1=0 means that the cA1 equals to the pure informed signals. S and F denote the original daily stock index and futures price, respectively. SW and FW denote the pure informed price on spot and futures. RS, RF, RSW, and RFW denote the daily continuous return and pure informed return on spot and futures, respectively.

Panel A: Price				
	S	F	SW	FW
Mean	6,639	6,632	6,640	6,632
Std. Dev.	1,432	1,443	1,421	1,433
ADF	-1.94	-1.76	-1.91	-1.99
Q^2 (24)	52258*	51219*	52740*	51828*
Trace		134*		133*
Panel B: Return				
	RS	RF	RSW	RFW
Mean	1.25%	1.28%	1.24%	1.26%
Std. Dev.	1.57%	1.83%	1.43%	1.55%
ADF	-51.54*	-56.63*	-31.21*	-32.26*
Q^2 (24)	1120*	1430*	2821*	2131*
Trace		1605		1414

a. Std. Dev. is standard deviation; Q^2(24) is the Ljung-Box statistics for serial correlations in the squared series; the ADF (Augmented Dickey Fuller) test is applied to test the null hypothesis of a unit root for the spot and futures prices and the returns.

b. Trace is the Johansen trace test, with the null hypothesis being that there is no co-integration.

c. * indicates Significant at the 1% level.

Table II. Summary of average hedge ratios for one hedge day

Three methods for estimating the optimal hedging ratios are used. They are ordinary least squares (OLS), error-correction (EC), and generalized autoregressive conditional heteroscedasticity (GARCH) models. In level 1 decomposition by wavelet analysis, let cD1=0 means that the cA1 equals to the pure informed signals. The cD1=1 means containing all the noise to equal to original signal. The cD1=1.1 means 110% noise and informed signal. The noise shows the different degree of the noise adding to the informed signal. Observations for estimating out of sample hedge ratios are from 60 days to 300 days.

Method	cD_1	Noise	Observations (J days) (%)					
			60	90	120	180	240	300
OLS	0	0%	89.271	88.962	88.701	88.455	88.293	88.137
	0.1	10%	89.140	88.830	88.570	88.323	88.160	88.001
	0.9	90%	83.614	83.231	83.009	82.760	82.560	82.333
	1.0	100%	83.014	82.615	82.393	82.136	81.931	81.698
	1.1	110%	82.480	82.066	81.843	81.578	81.368	81.130
EC	0	0%	89.258	88.938	88.657	88.389	88.235	88.056
	0.1	10%	89.383	89.041	88.737	88.441	88.275	88.085
	0.9	90%	85.888	85.402	85.035	84.598	84.322	84.011
	1.0	100%	85.402	84.903	84.538	84.092	83.806	83.486
	1.1	110%	84.960	84.449	84.084	83.630	83.336	83.009
GARCH		100%	86.015	86.245	85.978	85.662	84.572	84.298

Note: The hedge ratios are presented by percentage.

Table III. Comparisons of hedging effectiveness for one Hedge day

Three methods for estimating the optimal hedging ratios are used. They are ordinary least squares (OLS), error-correction (EC), and generalized autoregressive conditional heteroscedasticity (GARCH) models. In level 1 decomposition by wavelet analysis, let cD1=0 means that the cA1 equals to the pure informed signals. The cD1=1 means containing all the noise to equal to original signal. The cD1=1.1 means 110% noise and informed signal. The noise shows the different degree of the noise adding to the informed signal. Observations for estimating out of sample hedge ratios are from 60 days to 300 days.

Method	cD_1	Observations					
		60	90	120	180	240	300
OLS	0	88.0452	88.0739	88.0388	88.1113	88.4572	88.4035
	0.1	88.0742	88.0978	88.0609	88.1373	88.4823	88.4313
	0.9	88.5949	88.5695	88.5263	88.6886	89.0144	89.0619
	1.0	88.5720	88.5455	88.4985	88.6790	89.0046	89.0620
	1.1	88.5386	88.5117	88.4606	88.6589	88.9843	89.0504
EC	0	88.1638	88.1781	88.1515	88.1616	88.4863	88.4273
	0.1	88.1825	88.1925	88.1624	88.1639	88.4881	88.4259
	0.9	88.7458	88.7598	88.7353	88.6975	88.9946	88.9958
	1.0	88.7602	88.7763	88.7523	88.7217	89.0164	89.0258
	1.1	88.7637	88.7816	88.7577	88.7358	89.0284	89.0652
GARCH		88.3444	88.5014	88.6064	88.5103	88.0863	89.0420

Note: The hedge effectiveness is presented by percentage.

Table IV. Comparisons of hedging effectiveness for two Hedge days

Three methods for estimating the optimal hedging ratios are used. They are ordinary least squares (OLS), error-correction (EC), and generalized autoregressive conditional heteroscedasticity (GARCH) models. In level 1 decomposition by wavelet analysis, let cD1=0 means that the cA1 equals to the pure informed signals. The cD1=1 means containing all the noise to equal to original signal. The cD1=1.1 means 110% noise and informed signal. The noise shows the different degree of the noise adding to the informed signal. Observations for estimating out of sample hedge ratios are from 60 days to 300 days.

Method	cD_1	Observations					
		60	90	120	180	240	300
OLS	0	92.3729	92.5280	92.5743	92.6384	92.8420	92.8530
	0.1	92.3850	92.5348	92.5784	92.6433	92.8463	92.8595
	0.9	92.0927	92.1437	92.1263	92.3095	92.5095	92.6075
	1.0	91.9876	92.0294	92.0023	92.2068	92.4090	92.5148
	1.1	91.8822	91.9162	91.8797	92.1045	92.3089	92.4214
EC	0	92.4202	92.5632	92.6041	92.6505	92.8437	92.8561
	0.1	92.4650	92.5807	92.6188	92.6545	92.8457	92.8565
	0.9	92.4476	92.5329	92.5289	92.5491	92.7095	92.7741
	1.0	92.4136	92.4767	92.4671	92.4968	92.6553	92.7260
	1.1	92.3581	92.4169	92.4020	92.4423	92.5993	92.6752
GARCH		88.3470	88.5554	88.5845	88.5546	88.0273	89.0182

Note: The hedge effectiveness is presented by percentage.

Table V. Comparisons of hedging effectiveness (5 Hedge days)

Three methods for estimating the optimal hedging ratios are used. They are ordinary least squares (OLS), error-correction (EC), and generalized autoregressive conditional heteroscedasticity (GARCH) models. In level 3 decomposition by wavelet analysis, let cD1-cD2-cD3=0-0-0 means that the cA3 equals to the pure informed signals. The cD1-cD2-cD3=1-1-1 means containing all the noise to equal to original signal. The cD1-cD2-cD3=0-0-0.1 means 10% noise and informed signal. The noise shows the different degree of the noise adding to the informed signal. Observations for estimating out of sample hedge ratios are from 60 days to 300 days.

Method	cD_1-cD_2-cD_3	Observations					
		60	90	120	180	240	300
OLS	0-0-0	95.6248	95.8360	95.8519	95.7491	92.8420	92.8530
	0-0-0.1	95.6822	95.8668	95.8812	95.7937	92.8463	92.8595
	1-1-1	94.6825	94.6884	94.6281	94.7998	92.5095	92.6075
EC	0-0-0	95.5407	95.7969	95.8433	95.7240	92.4090	92.5148
	0-0-0.1	95.6047	95.8210	95.8613	95.7542	92.3089	92.4214
	1-1-1	95.1994	95.2540	95.2036	95.2493	92.8437	92.8561
GARCH		88.2614	88.4893	88.6437	88.5674	92.8457	92.8565

Note: The hedge effectiveness is presented by percentage.

Table VI. Comparisons of hedging effectiveness (10 hedge days)

Three methods for estimating the optimal hedging ratios are used. They are ordinary least squares (OLS), error-correction (EC), and generalized autoregressive conditional heteroscedasticity (GARCH) models. In level 4 decomposition by wavelet analysis, let cD1-cD2-cD3-cD4=0-0-0-0 means that the cA4 equals to the pure informed signals. The cD1-cD2-cD3-cD4=1-1-1-1 means containing all the noise to equal to original signal. The cD1-cD2-cD3-cD4=0-0-0-0.1 means 10% noise and informed signal. The noise shows the different degree of the noise adding to the informed signal. Observations for estimating out of sample hedge ratios are from 60 days to 300 days.

Method	cD_1-cD_2-cD_3-cD_4	Observation days (J)					
		60	90	120	180	240	300
OLS	0-0-0-0	96.9043	97.5008	97.5798	97.6258	97.6366	97.6433
	0-0-0-0.1	97.2205	97.5337	97.6445	97.7062	97.7202	97.7340
	1-1-1-1	96.0653	96.0584	95.9990	96.1256	96.1403	96.2251
EC	0-0-0-0	96.8369	97.4679	97.5555	97.6203	97.6230	97.6483
	0-0-0-0.1	97.2720	97.4861	97.5644	97.6806	97.6722	97.6958
	1-1-1-1	96.6560	96.6854	96.6435	96.6611	96.6448	96.6669
GARCH		88.0292	88.3192	88.3718	88.4622	86.9230	89.0239

Note: The hedge effectiveness is presented by percentage.

Table VII. Comparisons of hedging effectiveness (16 hedge days)

Three methods for estimating the optimal hedging ratios are used. They are ordinary least squares (OLS), error-correction (EC), and generalized autoregressive conditional heteroscedasticity (GARCH) models. In level 1 decomposition by wavelet analysis, let cD1=0 means that the cA1 equals to the pure informed signals. The cD1=1 means containing all the noise to equal to original signal. The cD1=1.1 means 110% noise and informed signal. The noise shows the different degree of the noise adding to the informed signal. Observations for estimating out of sample hedge ratios are from 60 days to 300 days.

Method	cD_1-cD_2-cD_3-cD_4	Observation days (J)					
		60	90	120	180	240	300
OLS	0-0-0-0	97.5461	98.1501	98.2463	98.3452	98.3875	98.3728
	0-0-0-0.1	97.8219	98.1280	98.2458	98.3550	98.3936	98.3889
	1-1-1-1	96.5728	96.4784	96.4008	96.4739	96.4602	96.5020
EC	0-0-0-0	97.4791	98.1297	98.2313	98.3315	98.3703	98.3706
	0-0-0-0.1	97.8856	98.1052	98.1870	98.3308	98.3547	98.3596
	1-1-1-1	97.1307	97.1159	97.0608	97.0531	97.0105	96.9887
GARCH		88.2526	88.0925	88.6232	88.888	88.6539	89.1111

Note: The hedge effectiveness is presented by percentage.

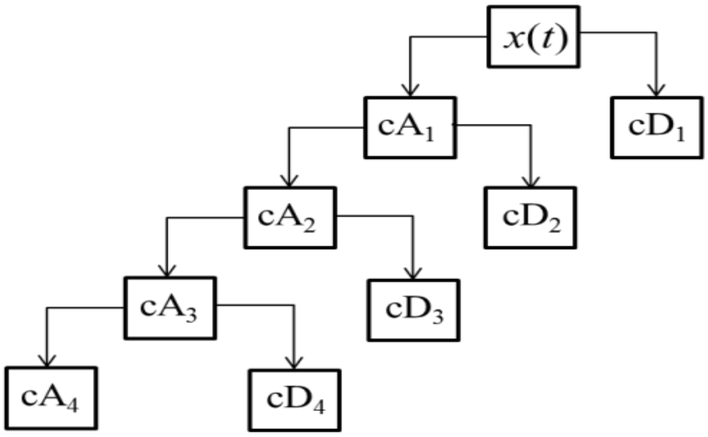

Figure 1 Analysis of a time series by wavelet decomposition tree: A 4 level filter bank

Note: This figure presents the wavelet decomposition tree. The original time series x(t) can be decomposed into wavelet scaling coefficients cA1 and wavelet coefficients cD1 in the first step. In the next step, the scaling coefficients which obtained in the first step is regarded as the original time series and decomposed as in the first step. This figure illustrates this procedure and continues to forth step.

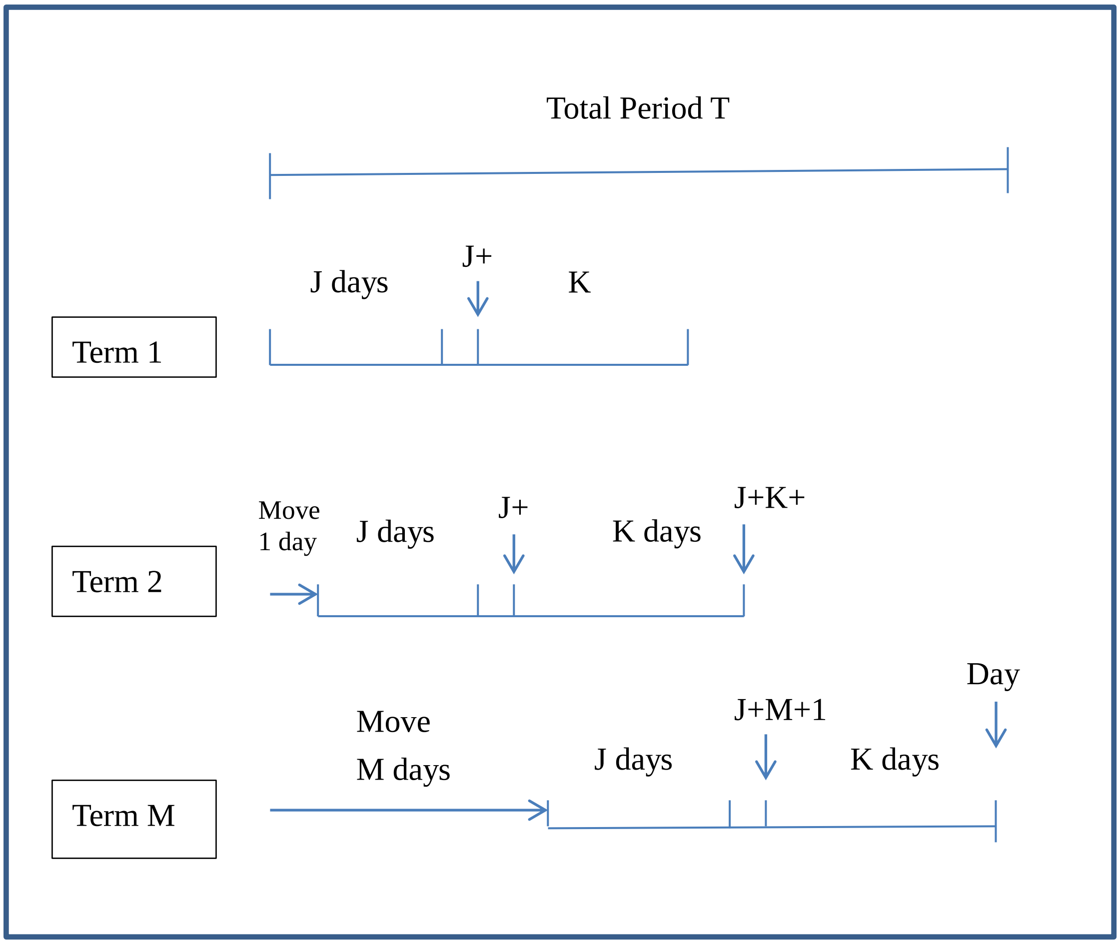

Figure 2 The moving window estimation method

Note: This figure presents the moving window estimation method that involves rolling over a particular number of samples to determine the series of out-of-sample rolling hedge ratios. For the total period T, J day observations are taken from the sample and use these observations to estimate hedge ratios for the next K hedge days. The calculation is repeated for the following period, using the nearest available J day observations to estimate the hedge ratios. By continually updating the model estimation to the end of the data set, T-J-K+1 hedge ratios are estimated for each model.

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The Application of Discriminants to Avoid Erroneous GM(1,1) Prediction

Chun-I CHEN [1]
Shou-Jen HUANG[2]

[1]Professor of Department of Industrial Management, I-Shou University,
No.1, Sec. 1, Syuecheng Rd., Dashu District, Kaohsiung City 84001,Taiwan, R.O.C.
TEL: +886-7-6577711 ext. 5522; FAX: +886-7-6578536
E-Mail: EddyChen@isu.edu.tw To whom all correspondence should be addressed

[2]PhD graduate of Department of Industrial Management, I-Shou University

ABSTRACT

The intrinsic defect of GM(1,1) that grey development coefficient a equals to zero will cause a significant and meaningless prediction errors in subsequent calculations. The researchers should be cautious when apply GM(1,1). Before applying GM(1,1), a pretest of raw data should be performed in order to avoid erroneous forecasting. In this research, a case of currency monthly exchange rate between HK dollar and US dollar from August, 2011 to January, 2012 has been shown to emphasize the importance of pretest of raw data.

Keywords: *Grey Prediction, Singular Phenomena, Discriminants, Currency Exchange*

1. Introduction

Grey theory was proposed by Professor Deng in early 1982 (Deng, 1982) and, subsequently has developed rapidly and been applied extensively in the field of forecasting science for various sectors, including economic, financial, industrial, agricultural, scientific and technological areas, during the last three decades (Wen, 2004). A number of scholars have diligently endeavored to improve the forecasting accuracy of GM(1,1). For example, a new formulation of background values using minimal calculations to construct a modified GM(1,1) model, proposed by Tan (2000) and Yao, Chi and Chen (2003), has increased prediction precision. A variable P value of a rolling GM(1,1) grey forecasting model was introduced by Chang, Lai and Yu (2005), which helped obtain more precise outcomes. Li, Yamaguchi and Nagai (2007) combined GM(1,1) with a Markov chain model to predict the business trends of Chinese international airlines and employed the Taylor approximation method to improve prediction precision. This new prediction model is named T-MCGM(1,1). Li, Yeh and Chang (2009) proposed the trend and potency tracking method (TPTM), in which they construct the optimized GM model, known as AGM(1,1), to improve forecasting quality. A new residual GM(1,1) model, introduced by Li and Wen (2011), uses a Markov state transition matrix to improve forecast accuracy by judging the sign of the residual predictive value first based on the distinctly reliable mechanism. Lin, Chiu, Lee and Lin (2012) presented the ultimate grey model, that is, EFGM(1,1). The mechanism of this model's excellent prediction ability is derived from Fourier series and exponential smoothing. Truong and Ahn (2012) presented a novel grey model, SAGM, for improving the prediction performance of the GM(1,1) model by addressing the identified disadvantages.

As the precision of the modified grey forecasting model has improved, the basic concepts of the grey forecasting model also need to be discussed further. In Chen and Huang's (2013) research, they found that if the grey development coefficient a equals zero, a meaningless predictive value will be obtained. Furthermore, Chen and Huang (2014) develop a set of discriminant to serve as pretest of raw data in order to avoid erroneous prediction. In this research, a case of currency monthly exchange rate between HK dollar and US dollar from August, 2011 to January, 2012 has been discussed to show the importance of pretest of raw data.

2. The Mathematical Model of GM(1, 1)

In Grey theory, the accumulated generating operation (AGO) technique is applied to reduce the randomization of the raw data. These processed data become monotonic increase sequence which complies with the solution of first order linear ordinary differential equation. Therefore, the solution curve would fit to the raw data with high precision. In the following section, the derivation of GM(1,1) is briefly described:

Step 1: Assume that the original series of data with *m* entries is

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(k), \cdots x^{(0)}(m)\}, \tag{1}$$

where raw material $X^{(0)}$ stands for the non-negative original historical time series data.

Step 2: Construct $X^{(1)}$ by one time accumulated generating operation (1-AGO), which is

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(k), \cdots x^{(1)}(m)\}, \tag{2}$$

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \qquad k = 1,2,\cdots,m.$

Step 3: The result of 1-AGO is monotonic increase sequence which is similar to the solution curve of first order linear differential equation. Therefore, the solution curve of following differential equation represents the approximation of 1-AGO data.

$$\frac{d\overset{\Lambda}{X}^{(1)}}{dt} + a\overset{\Lambda}{X}^{(1)} = b, \tag{3}$$

where Λ represents Grey predicted value. The *a* and *b* are model parameters. $\overset{\Lambda}{X}^{(1)}(1) = x^{(0)}(1)$ is the corresponding initial condition.

Step 4: The source model can be obtained

$$x^{(0)}(k) + az^{(1)}(k) = b, \qquad k = 2,3,4\cdots \tag{4}$$

From Eq.(4), by the least square method, the model parameters a and b become

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_N, \tag{5}$$

where B and YN are defined as follows:

$$B=\begin{bmatrix}-z^{(1)}(2) & 1\\ -z^{(1)}(3) & 1\\ \vdots & \vdots\\ -z^{(1)}(m) & 1\end{bmatrix},\qquad Y_N=\begin{bmatrix}x^{(0)}(2)\\ x^{(0)}(3)\\ \vdots\\ x^{(0)}(m)\end{bmatrix}, \tag{6}$$

By expansion of Eq.(4), the model parameters a and b are also expressed in the following parametric forms:

$$a=\frac{CD-(n-1)E}{(n-1)F-C^2}\qquad b=\frac{DF-CE}{(n-1)F-C^2} \tag{7}$$

where C, D, E, and F are as follow:

$$C=\sum_{k=2}^{n} z^{(1)}(k)\qquad\qquad D=\sum_{k=2}^{n} x^{(0)}(k)$$

$$E=\sum_{k=2}^{n} z^{(1)}(k)x^{(0)}(k)\qquad F=\sum_{k=2}^{n}[z^{(1)}(k)]^2 \tag{8}$$

Step 5: Solve Eq.(3) together with initial condition, and the particular solution is

$$\hat{X}^{(1)}(k+1)=(x^{(0)}(1)-\frac{b}{a})e^{-ak}+\frac{b}{a},\qquad k=2,3,4,\cdots \tag{9}$$

Hence, the desired prediction output at k step can be estimated by inverse accumulated generating operation (1-IAGO) which is defined as

$$\hat{X}^{(0)}(k+1)=\hat{X}^{(1)}(k+1)-\hat{X}^{(1)}(k)=(1-e^{a})(x^{(0)}(1)-\frac{b}{a})e^{-ak},\ k=2,3,4.. \tag{10}$$

3. The mathematical formulation of singular phenomena on GM(1,1)

Based on the previous discussion (Chen and Huang, 2013), we hope to determine how researchers could avoid the singular phenomena that cause significant distortion of the prediction function on GM(1,1) if the number of sampling observation data points is greater than or equal to five. The authors proposed a formula by way of mathematical induction as follows:

Proposition: Given the original series of data with *k* entries is

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(k)\} \tag{11}$$

where raw material $X^{(0)}$ stands for the non-negative origin historical time series data.

There exist two different formulas:

(1) If *k* is even, then the numerator is given by

$$\mathrm{Y}^{k} = \sum_{\mathrm{n}=1}^{\frac{k}{2}} (\frac{k}{2} - \mathrm{n})(x_{\mathrm{n}+1} - x_{k-\mathrm{n}+1}) \tag{12}$$

(2) If *k* is odd, then the numerator is given by

$$\mathrm{Y}^{\mathrm{k}} = \sum_{\mathrm{n}=0}^{\mathrm{k}-2} [\mathrm{k} - 2(\mathrm{n}+1)]\mathrm{x}_{\mathrm{n}+2} \tag{13}$$

For example,

$$\mathrm{Y}^{k=8} = 3x_2 + 2x_3 + x_4 - x_6 - 2x_7 - 3x_8$$

and

$$\mathrm{Y}^{k=9} = 7x_2 + 5x_3 + 3x_4 + x_5 - x_6 - 3x_7 - 5x_8 - 7x_9$$

where $x_2 = x^{(0)}(2)$, $x_3 = x^{(0)}(3)$, $x_4 = x^{(0)}(4)$, $x_5 = x^{(0)}(5)$, $x_6 = x^{(0)}(6)$,

$x_7 = x^{(0)}(7), x_8 = x^{(0)}(8)$ and $x_9 = x^{(0)}(9)$.

We note that if $\mathrm{Y}^{k} = 0$, this implies the grey development coefficient $a = 0$. The mathematical formulation is powerful to view when the singular phenomena occur. (Chen and Huang, 2014)

4. Numerical illustration

Using manual and electronic calculations (i.e., Excel and MATLAB), we observe that a is extremely close to zero under certain permutations of raw data. However, after integrating a into the grey development coefficient parametric equation, we observed that a should be zero, which was verified in our previous study (Chen and Huang, 2013). In this section, a case of currency monthly exchange rate between HK dollar and US dollar from August, 2011 to January, 2012 has been discussed to show the importance of pretest of raw data.

To examine the precision of the model proposed in this study, further tests are required to determine the error between the forecast value and actual value. Therefore, we adopted three statistical measures, specifically, relative percentage error (RPE) analysis, average relative percentage error (ARPE), and rolling grey model (RGM) error analysis, to assess the model's precision.

The three measures are defined as follows:

$$RPE = \varepsilon(k) = \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \times 100\% \ , \tag{14}$$

where k=2,3,4,⋯,m,

$x^{(0)}(k)$ is the actual value and $\hat{x}^{(0)}(k)$ is the forecast value.

The total model precision can be defined using the average relative percentage error (*ARPE*) as follows:

$$ARPE = \varepsilon(avg) = \frac{1}{m}\sum_{k=2}^{m}\left|\varepsilon(k)\right| \times 100\%, \tag{15}$$

where k=2,3,4,⋯

The *ARPE* should exclude $\varepsilon(1)$ as it is zero.

$$RGM\big(\varepsilon(RGM, k+1)\big) = \frac{x^{(0)}(k+1) - \hat{x}^{(0)}(k+1)}{x^{(0)}(k)} \times 100\% \ , \tag{16}$$

where $k+1 \leqq m$,

$x^{(0)}(k+1)$ is the actual value and $\hat{x}^{(0)}(k+1)$ is the forecast value.

The RGM uses the forward sequence data to calculate the residual percentage and is a reasonable model for determining the variation tendency because the RGM parameters are updated continuously. The model is reconstructed when a new observation is obtained.

Practical case: The foreign exchange rate of Hong Kong against the U.S. dollar from August 2011to January 2012

As competing U.S. trade partners, both Hong Kong and Taiwan rely on exports as their primary economic activities. Therefore, changes in the U.S. dollar exchange rate have profound and diverse effects on their trade with the U.S. The trend of Hong Kong's foreign exchange rate against the U.S. dollar has been used to examine the accuracy of the GM(1,1) grey prediction model under four-point rolling.

Table 1 shows the changes in the Hong Kong dollar to U.S. dollar exchange rate between August 2011 and January 2012.When the series sampled was (7.797, 7.793, 7.777, 7.781) as observation data, where the second and fourth values are not identical, the GM(1,1) demonstrated superior grey prediction abilities, with an ARPE($\varepsilon(avg)\%$) of 0.06%.Additionally, the prediction error RGM($\varepsilon(RGM,k+1)\%$)of the exchange rates in December 2011 was0.07%. By contrast, singular phenomenon occurs when the exchange rates from September 2011 to December 2011 (7.793, 7.777, 7.781,7.777) has been used to conduct four-point rolling prediction of the exchange rates in January 2012 through EXCEL and MATLAB calculations. This was because the exchange rates for both October 2011 and December 2011 were 7.777; that is, the second and fourth values in the series were identical. This caused the errors of ARPE($\varepsilon(avg)\%$) and RGM($\varepsilon(RGM,k+1)\%$) to reach 7.69% and 7.51% respectively; however, the errors decreased to 0.02% and 0.19% after the L'Hopital's rule was applied.

Table 1: The Prediction of Exchange Rate between HK and US Dollar from 2011-08 to 2012-01 by the Grey Model GM(1,1) source:www.dgbas.gov.tw

k	1	2	3	4	5	6		
month	2011-08	-09	-10	-11	-12	2012-01	unit:$H.K./$1U.S.	
Actual value	7.797	7.793	7.777	7.781	7.777	7.763	a	b
$\hat{x}^{(0)}(1:4)$	7.797	7.8	7.8	7.8	7.8		0.0008	7.799
	$\varepsilon(k)\%$	0.04%	0.09%	0.04%				$\varepsilon(\text{avg})$ =0.06%
				$\varepsilon(RGM,k+1=5)$=0.07%				
$\hat{x}^{(0)}(2:5)$ by EXCEL		7.793	7.18	7.18	7.18	7.18	7.216×10^{-16}	7.778
	$\varepsilon(k)\%$		7.68%	7.72%	7.68%			$\varepsilon(\text{avg})$ =7.69%
					$\varepsilon(RGM,k+1=6)$=7.51%			
$\hat{x}^{(0)}(2:5)$ by MATLAB		7.793	7.18	7.18	7.18	7.18	7.216×10^{-16}	7.778
	$\varepsilon(k)\%$		7.68%	7.72%	7.68%			$\varepsilon(\text{avg})$=7.69%
					$\varepsilon(RGM,k+1=6)$=7.51%			
$\hat{x}^{(0)}(2:5)$by L'Hopital's Rule		7.793	7.778	7.778	7.778	7.778		7.778
	$\varepsilon(k)\%$		0.02%	0.03%	0.02%			$\varepsilon(\text{avg})$=0.02%
					$\varepsilon(RGM,k+1=6)$=0.19%			

5. Conclusions

The grey development coefficient a becomes close to but not equal to zero after computerized calculations because of computer floating-point errors, which result in an indeterminate form $0 \cdot (-\infty)$ in the GM(1,1) grey prediction equation and significant errors in the grey prediction values. We recommend that the discriminant needs to be used in advance to avoid erroneous prediction. Scholars should use the necessary and sufficient conditions on the prediction equation of GM(1,1) to avoid the occurrence of singular phenomena. Therefore, the discriminant should be applied prior to all calculation. The discriminant is summarized as

$$k\text{=Even,} \quad \sum_{\mathrm{n}=1}^{\frac{k}{2}} \left(\frac{k}{2} - \mathrm{n}\right)(x_{\mathrm{n}+1} - x_{k-\mathrm{n}+1}) = 0$$

$$k\text{=odd,} \quad \sum_{\mathrm{n}=0}^{\mathrm{k}-2} [k - 2(\mathrm{n}+1)] x_{\mathrm{n}+2} = 0$$

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