A new dynamic hedging model with futures: Kalman filter error correction model

Chien-Ho Wang*
National Taipei University

Chang-Ching Lin †
Academia Sinica

Shu-Hui Lin ‡
National Changhua University of Education

Hung-Yu Lai §
E. Sun Bank

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Abstract

This paper investigates the hedging effectiveness in stock index futures markets by a new hedging model: Kalman filter error correction (KF-ECM) model. Kalman filter state space model proposed by Chang, Miller and Park (2009) is used to extract the common trend among Taiwan weighted stock index (TAIEX) and TAIEX futures. After the common trend is obtained, we combine common stochastic trend with traditional error correction model. We estimate KF-ECM hedging model and compare its hedging effectiveness with other hedging models including OLS, GARCH, and vector error correction model. The empirical results indicate that Kalman filter error correction

*Corresponding author: Chien-Ho Wang, Department of Economics, National Taipei University, 3F36 Social Science Building, 151 University Road, San Shia, Taipei county, 237, Taiwan. Email: wangchi3@mail.ntpu.edu.tw.

†Institute of Economics, Academia Sinica, 115 NanKang Taipei Taiwan. Email: lincc@econ.sinica.edu.tw.

‡Department of Business Education, National Changhua University of Education, 2, Shi-Da Rd., Changhua 500, Taiwan. Email: shlin@cc.ncue.edu.tw.

§E. Sun Bank, Email: fulspper@yahoo.com.tw.

hedging model performs more effectively than other constant and dynamic hedging models.

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1 Introduction

Since the introduction of stock index futures in late 1970s, the stock index futures become a popular hedging instrument in stock markets. How to choose the optimal hedge strategy becomes an important issue in risk management. Previous research has found different kinds of econometric models for static hedging effectiveness. However, the hedging effectiveness will depend on characteristics of stock markets, hedging models and time period.

Earlier hedge studies use traditional ordinary least square (OLS) regression to estimate the optimal hedging ratio and hedging efficiency (Johnson 1960; Ederington 1979). Although OLS method can catch the relationship between stock index and its futures, some of the stock characteristics like nonstationary and conditional volatility are not considered by OLS model. Ghosh (1993a; 1993b) finds the unit roots persent in stock index and its futures. For handling the nonstationary in hedging model, Ghosh (1993a; 1993b) proposes the error correction (ECM-ML) hedging model to estimate hedging performance. Even though error correction hedging model may model the relationship between spot stock index and stock index futures, the long run relationship between them cannot be extracted accurately. It will cause loss of hedging effectiveness with error correction hedging model. In order to correct the loss of hedging effectiveness, the generalized autoregressive conditional heteroskedasticity (GARCH)model with error correction approach (eg. Hsu, Tseng and Wang 2008) has been used to calculate hedging effectiveness. Error correction hedging model with GARCH may increase the hedging effectiveness by minimum the variance, but Miffre (2004) finds that adding GARCH has limit improvement for hedging effectiveness.

This paper investigates the hedging effectiveness in stock index futures market by a new hedging model: Kalman filter error correction (KF-ECM) model. We use Kalman filter state space model proposed by Chang, Miller and Park (2009) to extract the best common stochastic trend from cointegration model. After the common trend obtained, we substitute common trend into error correction model to estimate hedging effectiveness. Because Kalman filter state space model can update all the information in the process of calculation. The best common trend extracted by Kalman filter is nearly true stock index pattern. We expect that the Kalman filter error correction hedging model will have more hedging effectiveness.

In this paper we compare Kalman filter error correction model with other hedging models including OLS, GARCH (1,1) and traditional error correction model in Taiwan weighted stock index (TAIEX). Benet (1992) finds the optimal hedging ratio is changing over time. Investigating the hedging effectiveness with fixed optimal hedging ratio is inadequate. In addition to compare the hedging effectiveness with staic hedging ratio, we will compare the effectiveness of dynamic hedging. We will separate the data set to three nonoverlapping periods and use the hedging effectiveness index (HEI) proposed by Park and Switzer (1995) to compare the hedging effectiveness among four hedging models. We can investigate whether the Kalman filter error correction hedging model outperform other hedging models.

The remainder of this study is organized as follows. The second section describes the characteristics and estimation methods of Kalman filter error correction model.The third section presents some empirical results with Kalman filter error correction model. We compare the common trend extracted by ECM-ML and KF-SSM. The effectiveness of different hedging models is studied in details. The conclusions of this study are presented in last section.

2 Kalman filter error correction model for hedging

Kalman (1960) proposes the state space model called Kalman filter to estimate parameters under unknown functional form of time series. Kalman filter is used to analyze time series in areonautical and electrical engineering, but the data structure used in Kalman filter must belong to stationary. To resolute this drawback, Chang, Miller and Park (2002) consider the state space model:

$$y_t = \beta x_t + u_t, \tag{1}$$

$$x_t = x_{t-1} + \upsilon_t, \tag{2}$$

where x_t is a scalar latent variable with fixed initial value x_0. y_t is a $m \times 1$ observable time series. u_t and υ_t are the sequences of independent, identically distributed (i.i.d.) errors with mean zero and variance Λ_0 and 1 respectively. For convenience, we may assume $y_t = \begin{pmatrix} S_t \\ F_t \end{pmatrix}$, where S_t is stock index and F_t is stock index futures. $\beta = \begin{pmatrix} \beta_s \\ \beta_f \end{pmatrix}$ and $u_t = \begin{pmatrix} u_{st} \\ u_{ft} \end{pmatrix}$ are coefficients and errors respectively. Equation (1) is called measurement equation. Equation (2) is called state space equation. Let y_t is the observed variable vector. y_t can be representative by an unobserved variable x_t. Kalman filter- state space model (KF-SSM) of Chang et. al. (2009) can be used to extract the best common stochastic trend between y_t and x_t. Let Θ_t be an sigma field generated by $y_1, \ldots, y_t$. The Kalman filter consists of prediction and updating steps. For the prediction step, we use the linear conditional expectations for mean and variance:

$$x_{t|t-1} = E(x_t|\Theta_{t-1}) = x_{t-1|t-1}, \tag{3}$$

$$y_{t|t-1} = E(y_t|\Theta_{t-1}) = \beta x_{t|t-1}. \tag{4}$$

and

$$\omega_{t|t-1} \equiv E[(x_t - x_{t|t-1})(x_t - x_{t|t-1})^{'}] = E[(x_{t-1} - x_{t-1|t-1})(x_{t-1} - x_{t-1|t-1})^{'}] + E[\upsilon_t \upsilon_t^{'}]$$

$$= \omega_{t-1|t-1} + 1, \tag{5}$$

$$\Sigma_{t|t-1} = E[(y_t - y_{t|t-1})(y_t - y_{t|t-1})^{'}] = E[(x_t - x_{t|t-1})(x_t - x_{t|t-1})^{'} \beta\beta^{'}] + E[u_t u_t^{'}]$$

$$= \omega_{t|t-1}\beta\beta^{'} + \Lambda, \tag{6}$$

When the new observation is added into information set Θ_{t-1}, the estimation of state space can be updating by updating equation:

$$x_{t|t} = x_{t|t-1} + \omega_{t|t-1}\beta^{'}\Sigma_{t|t-1}^{-1}(y_t - y_{t|t-1}), \tag{7}$$

and

$$\omega_{t|t} = \omega_{t|t-1} - \omega_{t|t-1}^{2}\beta^{'}\Sigma_{t|t-1}^{-1}\beta. \tag{8}$$

Under x_t is I(1) process, Lemma 2 of Chang et. al. (2009) is given the prediction and updated steps for KF-SSM model.

$$x_{t|t-1} = \frac{\beta^{'}\Lambda^{-1}}{\beta^{'}\Lambda^{-1}\beta}\left[y_t - \sum_{k=0}^{t-1}\left(1 - \frac{1}{\omega}\right)^{k}\Delta y_{t-k}\right] + \left(1 - \frac{1}{\omega}\right)^{t-1} x_0. \tag{9}$$

When cointegrated state space model is decomposed by permanent and transitory components, Chang et. al. (2009) suggest an obvious permanent-transitory decomposition:

$$y_t = y_t^P + y_t^T,$$

$$y_t^P = \beta x_{t|t-1} \quad \text{and} \quad y_t^T = y_t - \beta x_{t|t-1},$$

where y_t^P and y_t^T are permanent and transitory components respectively. Because y_t^P is a function of y_t and y_t is a series with I(1) stochastic common trend, the common trend can be extracted by maximum likelihood estimation:

$$\ln L(\theta) = -\frac{n}{2}\log\det\Sigma - \frac{1}{2}\mathrm{tr}\Sigma^{-1}\sum_{t=1}^{n}\varepsilon_t\varepsilon_t^{'}, \tag{10}$$

$$\varepsilon_t = y_t - y_{t|t-1}, \tag{11}$$

where Σ is the steady state value of $\Sigma_{t|t-1}$. After we obtain the common trend, the measure equation (1) can be rewritten as

$$S_t = \beta_s x_t + u_{st} \tag{12}$$

$$F_t = \beta_f x_t + u_{ft}. \tag{13}$$

Because x_t is a latent variable, we rewrite x_t as a function of Equation (13),

$$x_t = \frac{F_t}{\beta_f} - \frac{u_{ft}}{\beta_f}. \tag{14}$$

Substituting Equation (14) into Equation (12), the stochastic common trend between stock index and stock index future can be expressed as:

$$S_t - \frac{\beta_s}{\beta_f} F_t = \left(u_{st} - \frac{\beta_s}{\beta_f} u_{ft} \right). \tag{15}$$

We propose a two stage method to estimate Kalman state space with error correction model:

1. Extract common trend with Kalman filter state space model.
2. Substitute common trend in Equation (15) into error correction model

$$\Delta S_t = \alpha_0 + \alpha_1 (u_{st} - \frac{\beta_s}{\beta_f} u_{ft}) + \beta \Delta F_t + \sum_{j=1}^{n} \delta_j \Delta F_{t-j} + \sum_{i=1}^{m} \xi_i \Delta S_{t-i} + e_t, \tag{16}$$

where β is the hedge ratio defined by Ghosh (1993). The new two stage method to estimate hedging ratio is called Kalman filter error correction (KF-ECM) estimator.

3 Empirical results

3.1 Data and common trends in stock and futures market

We study the main nineteen industries stock indexes in the Taiwan stock exchange (TWSE). The sample period is from January 05, 1995 to February 28, 2009 with daily base [1]. Table 1 show the percentage of every industry occupied in TAIEX.

[1] We delete weekends and holidays in series

Table 1: Percentage of nineteen largest industrial sectors

industry	percentage	industry	percentage
electrical	54.559%	building material and construction	1.098%
finance and insurance	12.537%	trading and consumers' goods	1.028%
plastic	8.327%	rubber	0.962%
iron and steel	3.277%	electrical machinery	0.816%
shipping and transportation	2.385%	automobile	0.603%
other	1.767%	electrical and cable	0.418%
textile	1.492%	glass and ceramic	0.302%
chemical and biotechnology	1.481%	tourism	0.294%
food	1.330%	paper and pulp	0.292%
cement	1.131%		

From: InfoWinner finance database

For compared with traditional cointegrated regression, The KF-SSM method proposed by Chang, Miller and Park (2009) is used to extract a best common trend among nineteen main industrial sectors in TWSE. Before we extract the best common trend, the series of stock prices of nineteen industrial sectors have their own trends in Figure 1.

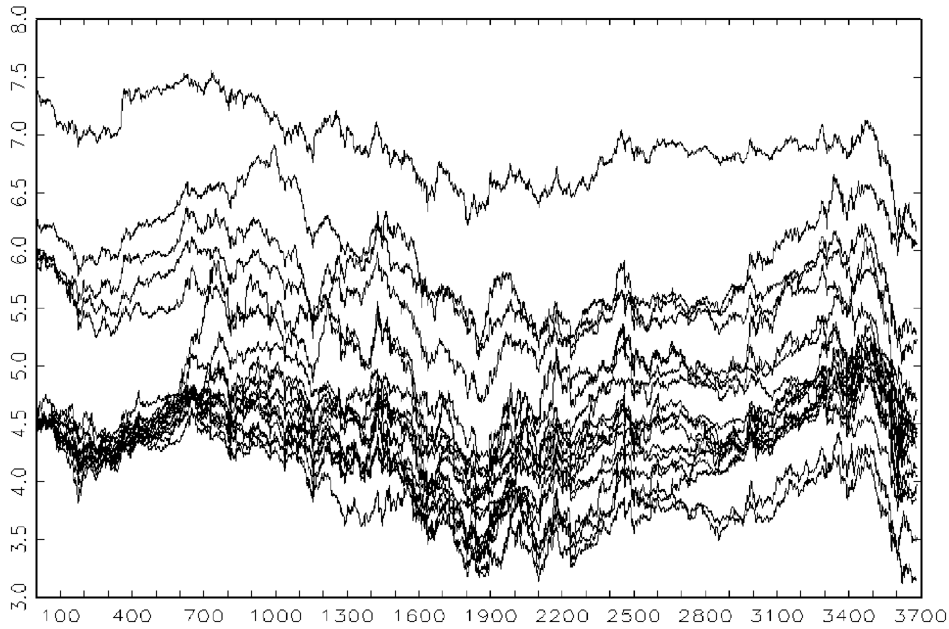

Figure 1: Stock indexes for 19 main industries (Jan. 01,1995-Feb.18,2009)

Table 2: parameter estimates by KF-SSM for 19 largest industries

parameters	estimate	standard error	parameters	estimate	standard error
β_1	0.0682	1.08×10^{-3}	β_{11}	0.0721	1.14×10^{-3}
β_2	0.0960	1.51×10^{-3}	β_{12}	0.0749	1.18×10^{-3}
β_3	0.0755	1.19×10^{-3}	β_{13}	0.0870	1.38×10^{-3}
β_4	0.0896	1.41×10^{-3}	β_{14}	0.0854	1.35×10^{-3}
β_5	0.0705	1.11×10^{-3}	β_{15}	0.0694	1.09×10^{-3}
β_6	0.0656	1.04×10^{-3}	β_{16}	0.0685	1.08×10^{-3}
β_7	0.0683	1.08×10^{-3}	β_{17}	0.1111	1.75×10^{-3}
β_8	0.0632	9.97×10^{-4}	β_{18}	0.0717	1.13×10^{-3}
β_9	0.0822	1.30×10^{-3}	β_{19}	0.0731	1.15×10^{-3}
β_{10}	0.0694	1.09×10^{-3}			

Parameters are cement, food , plastic, textile, electrical machinery, electrical and cable, chemical and biotechnology, glass and ceramic, paper and pulp, iron and steel, rubber, automobile, electrical, building material and construction, shipping and transportation, tourism, finance and insurance, trading and consumers' goods, other in order.

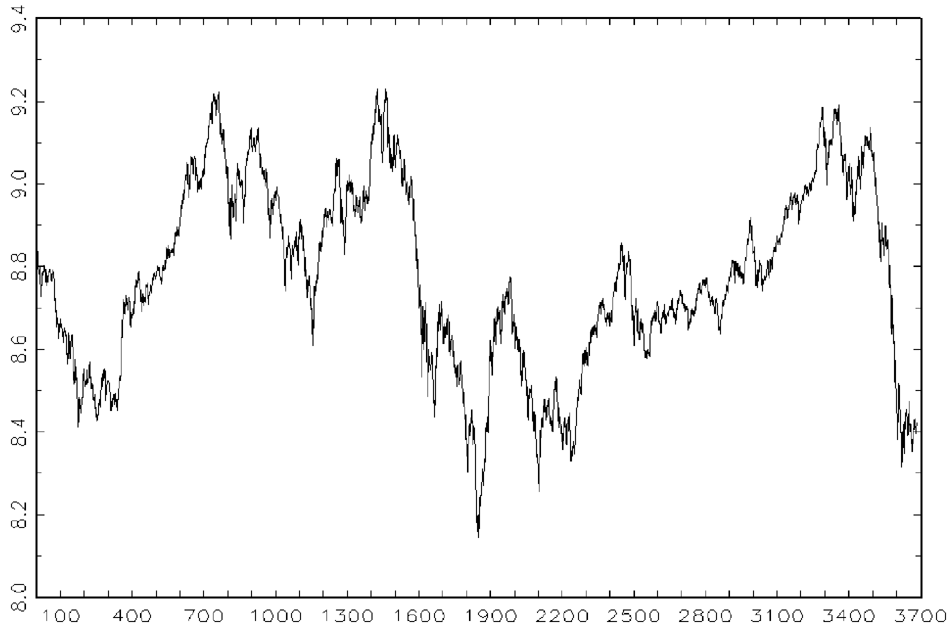

Figure 2: logarithms of TAIEX (Jan. 01,1995-Feb. 18,2009)

After the best common trend is extracted by KF-SSM, we may compare the common trend with the TAIEX and cointegration result. Figure 2 and 3 show the TAIEX, common trend extracted by KF-SSM and ML-ECM.

The common trend nearly have the same attitude and direction as TAIEX, but the common trend from error correction method cannot follow the true path of Taiwan stock index. The reasons to generate the difference are that KF-SSM method only extract one best common trend, but ML-ECM method extract all possible trends and choose the best one. If a lot of time series share the same stochastic trend, KF-SSM have a better performance than ML-ECM. Parameter estimates and their standard errors for β using KF-SSM are given in Table 2. From Table 2 we find that common trend impacts on every industrial stock indexes. When the common trend changes, finance and insurance industry will have largest influence among all industries.

When nineteen main industrial sector stock indexes share one common stochastic trend, the long run equilibrium exists in nineteen industrial sectors stocks. The common stochastic trend extracted by KF-SSM is similar with TAIEX. This similarity imply that the same factors drive the fluctuations in KF-SSM stochastic trend and TAIEX. Because we use KF-SSM to estimate common stochastic trend, the weight for every industrial sector is same.

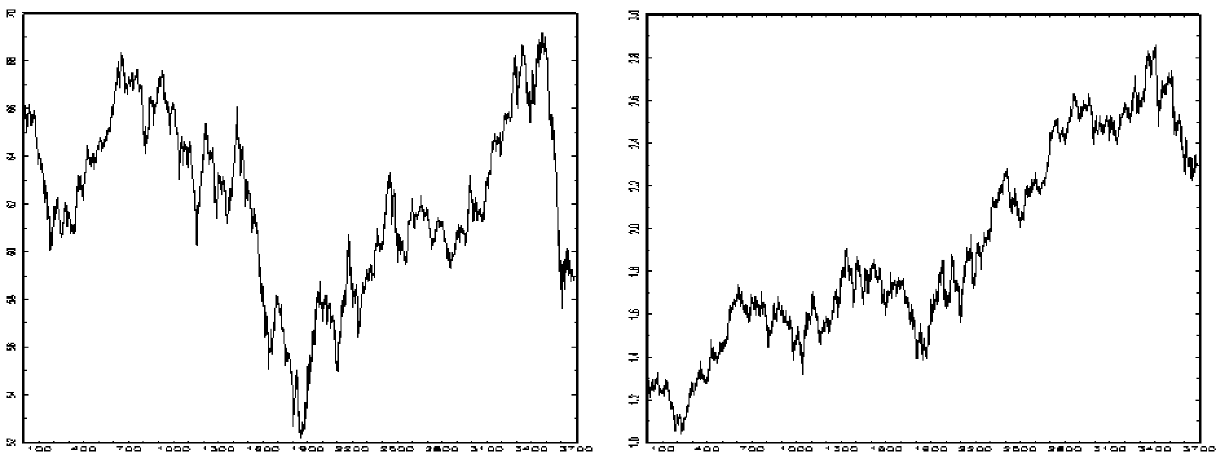

Figure 3: (a)common trend extracted by KF-SSM (b)common trend extracted by ML-ECM

The common trend can affect the fluctuations of every industrial sector stock indexes by parameters of state variables. Some of important factors will impact the stock prices and indexes like international economic condition, fundamentals of every industries and earnings and dividends. The common stochastic trend can response these important factors. Because of same trend between KF-SSM extracted and TAIEX index, Taiwan stock index can be explained by these important factors efficiency. We may conclude that long run relationship extracted by KF-SSM is better than traditional maximum likelihood error correction model (ML-ECM).

From the analysis above, we find that common trend among nineteen industrial sector indexes is similar with TAIEX. we will investigate when spot or futures extracts common stochastic trend with industrial sector indexes, whether these long-run relationships exists. Because the four largest industrial sector indexes occupy 78.7% of TAIEX, the variation of four largest industrial sector indexes will have huge impact on TAIEX. Three common trends are extracted by four industrial sector indexes, four industrial sector indexes with spot indexes and four industrial sector indexes futures indexes separately in Figure 4. In Figure 4 we can find that common trend series extracted by four industrial sector indexes with spot is nearly identical as four industrial sector indexes with futures. When the spot and futures have difference prices, the investor engage in arbitrage. The difference between spot and futures will disappear immediately. That is the main reason why four industrial sector indexes with spot is nearly similar with four industrial sector indexes with futures. If we compare common stochastic trend by four largest industrial sector indexes with four industrial sector indexes with spot or futures in Table 4, the difference between common

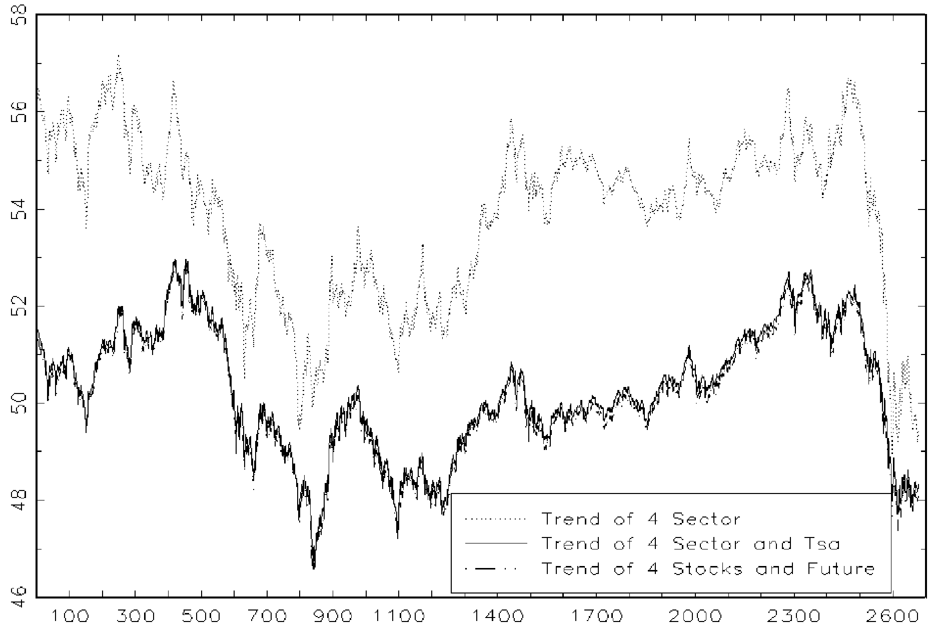

Figure 4: common trends extracted by Kalman filter

trends of four main industrial sector index and four main industrial sector index with spot or futures are the influence by spot index or futures. For comparison these three series, we need to demean all series in advance. After demeaning the three common trends, from Figure 5 we can find common trend by four largest industrial sector indexes can reach the peak or trough early than common trend extracted by spot with four industrial sector index or futures with four industrial sector index. When the economic fundamentals change, the four main industrial sectors will choose a better production strategy under new economic situation. The stochastic common trend extracted by four main industrial sector indexes will lead the variation in spot and futures.

3.2 Application in hedging ratio

Since the Kansas City Board of Trade issue Value-line stock index futures, stock index futures become main instruments to hedge risk at stock market. For choosing a best hedging strategy in stock market, difference hedging models had been constructed. Although there are a lot of kinds of hedging models in literatures, no any hedging model is dominated to others. Because KF-SSM can extract better common trend than ML-ECM, we may use Kalman filter error correction model (KF-ECM) to build hedging model. After KF-ECM

Figure 5: demeaned common trends

hedging model is estimated, we can compare KF-ECM model with the other hedging models appeared in literatures.

For simplifying our analysis, we assume the only hedging instrument in stock market is futures contract. The hedge portfolio consist of spot and futures for short hedge. When investors engage in hedging activity in stock market, investors will buy the futures contract. Let f_t and s_t be the daily price changes of the futures price ,F_t, and spot price, S_t, then hedge ratio (HR) can be defined as:

$$HR = \frac{Cov(s_t, f_t)}{Var(f_t)}. \tag{17}$$

Some research about optimal hedge often assume hedge ratios fixed, but hedge ratios will depend on the sample period. If we keep the hedge ratios fixed, the hedge effectiveness cannot be measured accurately. For avoiding fixed hedge ratios, we use rolling regression and out of sample prediction technology proposed by Chiu, Wei, Wu and Chiou (2004). First, we choose the first $\frac{2}{3}$ of all sample to estimate hedge ratio for hedging models. After the hedge ratio is obtained, the hedging effectiveness (HE) proposed by Park and Switzer

(1995) can be calculate by:

$$HE = \frac{Var(U) - Var(H)}{Var(U)} = 1 - \frac{Var(H)}{Var(U)}, \tag{18}$$

where $Var(U)$ is the variance of stock portfolio without hedging. $Var(H)$ is the variance of stock portfolio with hedging by futures. Hedging effectiveness is measured the variation of basic risk before and after hedge. If the hedging scheme is effective, hedging effectiveness will be near zero. When the hedging effectiveness is obtained, we add next one sample point and repeat all steps to calculate hedging effectiveness for remained $\frac{1}{3}$ sample. Second, we repeat to calculate hedge ratios for last $\frac{1}{3}$. when every subsample hedge ratio is obtained, we use the hedge ratio to execute hedging strategy and compare the hedging result with the true sample of next period. After all hedging effectiveness is calculated, We can find the hedging effectiveness indexes (HEI):

$$HEI = \frac{\sum_{j=1}^{M} HE^{(j)}}{M}, \tag{19}$$

where M is the last $\frac{1}{3}$ sample size. Finally, the hedging effectiveness indexes from all hedging models are obtained, we can compare the hedging models by hedging effectiveness indexes.

Because Taiwan stock futures transaction begin from 1998, we choose the daily spot and futures indexes of Taiwan exchange board from July 21, 1998 to February 28, 2009. The hedging models considered in this paper are ordinary least square (OLS) model, GARCH(1,1) model, Error correction model (ECM) and Kalman filter error correction model (KF-ECM).

1. OLS model

$$s_t = \alpha + \beta f_t + \varepsilon_t. \tag{20}$$

2. GARCH(1,1) model

$$s_t = \alpha + \beta f_t + \varepsilon_t \tag{21}$$

$$\varepsilon_t | \Psi_{t-1} \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2$$

3. Error Correction model

$$s_t = \alpha_0 + \alpha_1 u_{t-1} + \beta f_t + \sum_{j=1}^{n} \delta_j f_{t-j} + \sum_{i=1}^{m} \xi_i s_{t-i} + e_t, \tag{22}$$

About the choose of lagged periods for ECM and KF-SSM models, we decide four optimal lagged periods by Akaike information criterion (AIC) for all f_t and s_t. Because we use error correction model to estimate hedging effectiveness, the augment Dickey-Fuller unit root tests is employed to test TAIEX and TAIEX futures series. ADF test results are presented in Table 8 at Appendix. TAIEX and TAIEX futures series reject the null hypothesis of the present of unit root.

Table 3: The model comparison of hedging effectiveness 1998-2009

Unhedged portfolio average variances	10986.843			
Hedging methods	OLS	GARCH(1,1)	Error correction	KF-ECM
Average variances after hedging	815.0664	821.962	682.5203	662.7874
Variance reduction improvement	92.58%	92.52%	93.79%	93.97%

Table 3 show the out of sample comparison of hedge effectiveness by different hedging models. We can find the hedge effectiveness of KF-ECM model is the best among all four hedging models.

From 1998 to 2009 Taiwan stock market had faced different financial crases. For comparing the hedge effectiveness under financial crases. We separate the data to three periods: 1998-2003, 2004-2006 and 2007-2009 [2]. Table 4, 5 and 6 show the measure of dynamic hedge effectiveness for four kinds of hedging models. We can find that KF-ECM model has the best hedge effectiveness among four models between 2003-2009, but ECM model has the best hedge effectiveness between 1998 to 2002. The possible explanation about this result is the two different crases occurred sequentially between 1998 to 2002. KF-ECM only can catch the stronger negative impact by single common trend, but ECM model can handle two common trends simultaneously.

[2] Asia financial crisis and network business bubble occurred from 1998 to 2002, and globe estate financial crisis occurred from 2007-2009.

Table 4: The dynamic hedging effectiveness 1998-2002

Unhedged portfolio average variances	8402.645			
Hedging methods	OLS	GARCH(1,1)	Error correction	KF-ECM
Average variances after hedging	901.8718	990.6766	681.9971	715.7856
Variance reduction improvement	89.26%	88.21%	91.88%	91.48%

Table 5: The dynamic hedging effectiveness 2003-2006

Unhedged portfolio average variances	4319.069			
Hedging methods	OLS	GARCH(1,1)	Error correction	KF-ECM
Average variances after hedging	360.6638	355.4934	302.3689	299.4813
Variance reduction improvement	91.64%	91.77%	93.00%	93.07%

Table 6: The dynamic hedging effectiveness 2007-2009

Unhedged portfolio average variances	17108.05			
Hedging methods	OLS	GARCH(1,1)	Error correction	KF-ECM
Average variances after hedging	1546.179	1543.957	1283.169	1281.133
Variance reduction improvement	90.96%	90.98%	92.50%	92.51%

4 Conclusion

This paper propose a Kalman filter error correction hedging model. We compare the hedging effectiveness with three other models: dynamic OLS , GARCH(1,1) and error correction hedging models. We find that Kalman filter error correction model outperform the others in hedging effectiveness no matter the in-sample or out-sample evidences are.

In this study result we can conclude that Kalman filter error correction model is substantially improved the hedging effectiveness. With this new hedging model, the investors may use for risk management.

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Appendix

Table 7: ADF statistics for 19 main industries

	Level		First Order Difference	
	$t-statistic$	$p-value$	$t-statistic$	$p-value$
food	-1.5642	0.5009	-54.9444*[1]	0.0001
plastic	-1.4990	0.5343	-58.6869*	0.0001
rubber	-1.9210	0.3228	-56.5553*	0.0001
tourism	-2.0622	0.2604	-56.0580*	0.0001
textile	-2.1399	0.2290	-58.7575*	0.0001
glass and ceramic	-2.0439	0.2681	-58.0603*	0.0001
chemical and biotechnology	-2.0275	0.2751	-55.9461*	0.0001
finance and insurance	-1.8249	0.3687	-59.5305*	0.0001
shipping and transportation	-2.3375	0.1602	-56.2063*	0.0001
cement	-1.8457	0.3586	-56.4446*	0.0001
trading and consumers' goods	-2.0596	0.2614	-57.2663*	0.0001
iron and steel	-1.6602	0.4515	-59.5254*	0.0001
other	-1.8629	0.3502	-56.1300*	0.0001
building material and construction	-1.4119	0.5780	-55.1727*	0.0001
electrical machinery	-1.6872	0.4378	-57.7978*	0.0001
electrical and cable	-1.6114	0.4766	-58.9115*	0.0001
electrical	-2.1371	0.2302	-30.2478*	0.0000
automobile	-1.3250	0.6200	-59.5133*	0.0001
paper and pulp	-2.8211	0.0554	-56.6592*	0.0001

* represents reject null hypothesis under 5% level.

Table 8: Augmented Dickey-Fuller test on TAIEX and TAIEX futures

	Level		First Order Difference	
	$t-statistic$	$p-value$	$t-statistic$	$p-value$
TAIEX	-1.769884	0.3959	-49.41151*	0.0001
TAIEX futures	-2.041421	0.2691	-53.64239*	0.0001