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RESEARCH NOTE

Price discovery in stock index: an ARDL-ECM approach in Taiwan case

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Abstract In this study, we examine the lead-lag effect between stock index futures and its spot markets in Taiwan by employing a newly developed econometrics method, ARDL-ECM approach. The advantage of applying such technique is to avoid earlier ambiguous causality testing procedure, and it can provide more clearly representation of a stable unidirectional price discovery process. By verifying intraday data, we find that the futures prices lead spot markets for about 30 min during the year 2004. Moreover, during the presidential election period which caused political turbulent in Taiwan, the function of future market supposed as the dominated role of price discovery becomes futility. Such findings are consistent with the 'surprising election outcomes' phenomenon.

Keywords ARDL-ECM · Lead-lag · Spot and futures · Stock index · Price discovery

1 Introduction

It is often believed that futures markets potentially provide a profound process of price discovery. Price discovery, according to Schreiber and Schwartz (1986), is the process in which markets attempt to reach equilibrium prices. Therefore, when observing the lead-lag effect, the price or movement of futures should contain useful information for its subsequent spot prices. Such effect illustrates how fast futures market reflects new information relative to its spot market. Under the perfectly efficient market hypothesis, where all available information is fully utilized, arbitrage activities will keep futures and spot price move more synchronous. These two markets should be contemporaneously correlated which is not consistent with the

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implication of lead-lag effect. In fact, due to market frictions (e.g. transaction costs and the market microstructure effects) non-synchronous movement between futures and spots markets are observed. The reasons for this lead-lag effect may be attributed by less restrictive regulation or lower transaction costs in futures markets. Comparing with its stock market, liquidity and financial leverage due to permissive short selling and marked to market trading may accelerate the speed of price discovery process.

Earlier empirical analyses focus on whether futures price is a determinant of spot price. The studies conclude inconsistent evidences and leave some ambiguous interpretations. Using different econometrical methods, there are many previous literatures to address that futures significantly tends to lead spot market. However, the studies apply incompletely unidirectional econometrical methodology, which means stock markets have a mild positive predictive ability (i.e. feedback effect) on futures returns. For instance, Kawaller et al. (1987) utilized the three-stage least-squares regression, and they indicate that S&P 500 futures price lead its spot price by 20–45 min while spot prices affect futures prices beyond 1 min. Besides, Finnerty and Park (1987) reports that stock index futures price changes are correlated with the stock index spot price changes. They claim no evidence for a causal relationship. Stoll and Whaley (1990) employs a standard time series analysis to research on the relationship between S&P 500 and MMI index futures returns. They conclude that S&P 500 and MMI index futures returns lead stock index returns by above 5 min on average. Also, they demonstrate that spot returns lead futures returns in the early inception period of futures trading. The standard time series analysis, however, fails to deal with short-run and long-run problem which is a crucial topic on equilibrium relationship based on arbitrage activities.

Addressed in this topic, cointegration test and error correction model may be most employed methodology which includes Engle and Granger two-step procedure and Johansen's methodology. These methods have fundamental drawback in dealing with causal relationships among variables. Kutner and Sweeney (1991) firstly examines Granger causality between the S&P 500 cash and futures markets. Wahab and Lashgari (1993) introduces cointegration and error correction model using the Engle–Granger two-step procedure to examine the temporal casual linkage between spots and futures markets for both S&P 500 and FTSE 100 indexes. On a daily data basis, they find that spot and futures prices are cointegrated and conclude the existence of feedback effect between spots and futures markets. Depending on the relative magnitudes of the error correction and lagged variable coefficients, they also conclude that the spot-to-futures lead appears to be more pronounced relative to the futures-to-spot lead. Many subsequent researches follow the same standard analysis procedure. For example, Pizzi et al. (1998) employs cointegration techniques to model two different contract expirations with spot market to explore price discovery in S&P 500 index. According to Engle–Granger causality test, the numbers of statistically significant lags in error correction model suggests that both the three- and six-month futures markets lead the spot market by at least 20 min, while spot markets lead both futures markets by 3–4 min. Such results deny the existence of unidirectional causation for futures-to-spot effect. In European financial markets, Shyy et al. (1996) applies the same error correction method and causality testing procedure to investigate causality between spot and futures markets for CAC index in France. Interestingly, they utilizes general method of moments to estimate Granger causality regression to find that the reverse causality from spots to futures which denied the general implication of lead lag effects.

The link between cointegration and causality stems from the fact that if spot and futures prices are cointegrated, then causality must exist in at least one direction and possibly in both directions. Cointegration implies that each series can be represented by an error correction model that includes last period's equilibrium error as well as lagged values of the first differences of each variable. Hence, temporal causality can be assessed by examining the statistical significance and relative magnitudes of the error correction coefficients and the coefficients on the lagged variables. In recent years, the error correction model is expanded by Hasbrouck (1995) applying common-factor model. Such transformation can measure each market's contribution to price discovery which defined as information sharing percentage on a presumed "implicit efficient price". However, the percentage illustration does not provide a definite description about direction of price discovery process while could not confirm the dominant role. For instance, Roope and Zurbrueg (2002) investigates causality between spots (Taiwan Stock Exchange Capitalization Weighted Stock Index, TAIEX) and its futures (TX) on the Taiwan stock market. The exogeneity testing results from error-correction model showed that there is a bidirectional relationship between these two markets. By applying Hasbrouck (1995) methodology, however, the TAIEX index contributes more (54.30%) to price discovery than does the TX futures market (45.70%). Furthermore, the Hasbrouck information bounds for these two markets are extremely wide (approximate around 10–90%), which suggests that both markets influenced by each other and unidirectional price discovery seem to be nonexistent.

By employing traditional error correction model, the existence of cointegration among time series of variables or the number of cointegrating vectors (linear combinations of variable which stabilize the system) does not help clarifying how an endogenous variable is driven by exogenous ones. Therefore, as reference above, earlier studies can not have the same implication of the unidirectional price discovery process which will be able to represent a more precise specification of lead-lag effect. In this article, the newly developed Autoregressive Distributed Lag approach considered by Pesaran et al. (2001, PSS), with its Bounds Testing procedure, is used to offer a satisfactory alternative. This advantageous approach has been gradually employing in many distinct academic areas, especially in many economic issues. In financial researches, Fedderke and Joao (2000) firstly applies PSS approach to examine the link between South African stock index futures markets and the underlying stock market index on a daily basis. PSS approach identifies exogenous, or the 'forcing', variables within the system, as well as long- and short-run driving intensity of them. More importantly, in the context of an Error-Correction Model (ECM), only one error-correction term will be present, which avoids confusion arising from having multiple cointegrating vectors. Unitary error-correction model acting as a sufficient condition for long run equilibrium will be appropriate estimated to show a unique and stable causal relationship between spot and futures market in Taiwan.

The remainder of this article is organized as follows. The following section briefly describes the data assessment and presents ARDL-ECM methodology. The subsequent section presents results of our analysis. The last section summarizes and concludes the study.

1.1 The data

The data of Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), TAIEX futures (TX), and mini-TAIEX Futures (MTX) are retrieved from the Taiwan Economic Journal (TEJ) on 10- min basis. Both TX and MTX futures, which are issued on a monthly cycle, are taken from the contracts with the closest date to maturity. Because the futures prices will converge to the spot prices close to expiration while will likely introduce bias estimation, contracts are rolled over to the next nearby contract three trading days before expiration. Rolling over too early will result in using less-liquid contracts. In fact, the volume of the nearby contracts usually remained highest among all traded contracts until 3 days before expiration.

Table 1 Descriptive statistics of 10- min price of TAIEX, TX, and MTX

	TAIEX	TX	MTX
First period			
Mean	3.813746	3.815280	3.815364
Median	3.811358	3.810434	3.810501
Maximum	3.852725	3.859318	3.859559
Minimum	3.772598	3.772688	3.772688
Std. Dev.	0.018786	0.019904	0.019957
Skewness	0.221134	0.391456	0.384948
Kurtosis	1.986321	2.110293	2.108938
Second period			
Mean	3.789226	3.789218	3.797015
Median	3.787106	3.787212	3.790397
Maximum	3.839855	3.839981	3.839527
Minimum	2.995679	2.995679	3.736743
Std. Dev.	0.072669	0.072662	0.027433
Skewness	−8.980104	−8.982728	−0.021045
Kurtosis	98.52051	98.55483	1.621286
Third period			
Mean	3.751405	3.747780	3.747793
Median	3.755321	3.749891	3.749891
Maximum	3.775987	3.774152	3.774152
Minimum	3.721167	3.717671	3.717587
Std. Dev.	0.015681	0.017080	0.017086
Skewness	−0.317838	−0.170383	−0.169015
Kurtosis	1.656853	1.638808	1.638966

The sample period, covering the 2004 presidential election period which resulted in political turbulent in Taiwan, is from 2 Jan 2004 to 17 Sep 2004. A set of trade and quote prices is filtered because they are likely to be erroneous or may not reflect the true trading cost that investors face in the market. The trades and quotes that are time stamped outside the regular Taiwan Stock Exchange (TWSE) trading hours, from 9:00 a.m. to 13:30 p.m., are also excluded. The tests are performed on three subsets of data. The first sub-period is from 2 Jan 2004 to 12 Mar 2004, the second sub-period is from 15 Mar 2000 to 14 May 2004, and the third sub-period is from 17 May 2004 to 17 Sep 2004. As Wahab and Lashgari (1993) points out, the lagged differences for the spot and futures prices, $\triangle St$ and $\triangle Ft$, must be purged of serial correlation to eliminate the effects of infrequent trading and the bid–ask price effect. The methodology that follows is similar to Stoll and Whaley (1990). The logarithms of the price series are analyzed in this study. Descriptive statistics of the price of the three indexes are given in Table 1.

2 Methodology

To examine the long-run relationship between spot and futures markets, we employ the newly developed autoregressive distributed lag (ARDL) cointegration framework

(Pesaran et al. 2001). This method avoids the classification of variables as $I(1)$ and $I(0)$ by developing bands of critical values which identifies the variables as being stationary or non-stationary processes. Unlike other cointegration techniques (e.g., Johansen's procedure) which require certain pre-testing for unit roots and that the underlying variables to be integrated are the same order, the ARDL model provides an alternative test for examining a long-run relationship regardless of whether the underlying variables are purely $I(0)$ or $I(1)$, even fractionally integrated. Therefore, the previous unit root testing of the variables is unnecessary. Moreover, traditional cointegration method may also suffer from the problems of endogeneity while the ARDL method can distinguish dependent and explanatory variables. Thus, estimates obtained from the ARDL method of cointegration analysis are unbiased and efficient, since they avoid the problems that may arise in the presence serial correlation and endogeneity. Note also that the ARDL procedure allows for uneven lag orders, while the Johansen's VECM does not.

A two-step procedure is used in estimating the long-run relationship. In the first step, we investigate the existence of a long-run relationship predicted by theory among the variables in question. The short and long-run parameters are estimated in the second stage, when if the long-run relationship is established in the first step.

Suppose that at the first stage, theory predicts that there is a long-run relationship among y and x. Without having any prior information about the direction of the long-run relationship among the variables, the following two unrestricted error correction (UEC) regressions are estimated considering each of the variables in turn as a dependent variable:

$$\Delta Y_t = \alpha_y + \sum_{i=1}^{n} \beta_{yi} \Delta Y_{t-i} + \sum_{j=0}^{n} \gamma_{yj} \Delta X_{t-j} + \theta_{y1} Y_{t-1} + \theta_{y2} X_{t-1} + \varepsilon_{yt} \tag{1}$$

$$\Delta X_t = \alpha_x + \sum_{i=1}^{n} \beta_{xi} \Delta X_{t-i} + \sum_{j=0}^{n} \gamma_{xj} \Delta Y_{t-j} + \theta_{x1} X_{t-1} + \theta_{x2} Y_{t-1} + \varepsilon_{xt} \tag{2}$$

F statistic is used for testing the existence of long-run relationships. The null hypothesis for testing the nonexistence of the first long-run relationship (i.e. $H_0 : \theta_{1y} = \theta_{2y} = 0$) is denoted by $F_y(y|x, y)$. Similarly, the F test for testing the null hypothesis for the nonexistence of the second long-run relationship (i.e. $H_0 : \theta_{1x} = \theta_{2x} = 0$) is denoted by $F_x(x|x, y)$. The F test has a nonstandard distribution which depends upon: (i) whether variables included in the ARDL model are to be $I(0)$ or $I(1)$, (ii) the number of regressors and (iii) whether the ARDL model contains an intercept and/or a trend. Two sets of critical values are reported in Pesaran et al. (2001): one set is calculated assuming that all variables included in the ARDL model are $I(1)$ and the other is estimated considering the variables are $I(0)$. If the computed F values fall outside the inclusive band, a conclusive decision could be drawn without knowing the order of integration of the variables. More precisely, if the empirical analysis shows that the estimated $F_y(.)$ is higher than the upper bound while $F_x(.)$ is lower than the lower bound, a unique and stable long-run relationship is tested to be valid. In this relationship, y is the dependent variable and x is 'long-run forcing' or exogenous variables.

If a stable long-run relationship is supported by the first step, then in the second stage, the augmented ARDL (m, p) model is estimated using the following:

$$Y_t = a + \sum_{i=1}^{m} b_i Y_{t-i} + \sum_{i=0}^{p} c_i X_{t-i} + u_t \tag{3}$$

Again the maximum of lags (n) in Eq. 1 must retain to determine the numbers of lags (m, p) in Eq. 3 selected by the Akaike Information Criterion (AIC) or Schwartz Bayesian Criterion (SBC) to determine the optimal structure for the ARDL specification. Having found associate ARDL model, the second stage involves estimate the long-run coefficients of dependent variable and the associated ARDL error correction models. Incorporating the long run and short-run terms into the model allows a more efficient estimate of the short-run coefficients. The conditional long-run model for dependent variable can be obtained from the reduced form solution of (3) as follows:

$$Y_t = \lambda a + \lambda \sum_{i=0}^{p} c_i X_t + \lambda u_t \tag{4}$$

where

$$\lambda = \frac{1}{1 - \sum_{i=1}^{m} b_i}$$

Meanwhile, the error correction representation of the ARDL model which involve the ECM term can be estimated by rearranging the original equation by OLS. Under the ARDL approach, the existence of a unique valid long run relationship among variables, and hence a sole error-correction term, is the basis for estimation and inference. Short run, or difference-based, relationship cannot be supported unless a unique and stable equilibrium relationship holds in significant statistical sense. Importantly, if the coefficients of the ECM term carry the expected negative sign and are highly significant, it will facilitate our empirical finding of cointegration as provided. The error-correction mechanism is described as follows:

$$\Delta Y_t = b_0 + \sum_{i=1}^{m-1} b_i \Delta Y_{t-i} + \sum_{i=0}^{p-1} c_i \Delta X_{t-i} - \left(1 - \sum_{i=1}^{m} b_i\right) ECM_{t-1} + \varepsilon_t \tag{5}$$

where

$$ECM_{t-1} = Y_t - \lambda a - \lambda \sum_{i=0}^{p} c_i X_t$$

3 Empirical results

In testing the null of no cointegration in Eq. 1, the critical issue is chosen as the maximum lag (n). Bahmani-Oskooee and Bohl (2000) has shown that the results of this first stage are usually sensitive to the order of VAR. In this study, we impose order of lag from 1 to 4 on the first difference of each variable and compute the F-statistic for the joint significance testing of a non-standard F distribution (Pesaran et al. 2001). If the null hypothesis is rejected, we then stop increasing order of lag length immediately and retain this order of lag as maximum lag for ARDL estimation. The results are reported in Table 2.

The null hypothesis of the nonexistence of the long-run relationship is rejected for all period. The results provide evidence for the existence of a long-run index and futures markets. Table 2 shows that spot market is the dependent variable in the first period and the third period, but futures market is the dependent variable in the second period. Therefore, merely considering short-term determination has not enough to explain the dynamics relationship between spot and futures market. Previously literatures indicate that the lead lag effect

Table 2 F-statistics for testing the existence of cointegration

	Maximum lag (n)	TAIEX–TX		TAIEX–MTX	
		TAIEX	TX	TAIEX	MTX
First period	3	5.9814*	4.5861	5.9058*	4.6016
Second period	1	1.4526	253.6944**	1.3223	449.6517**
Third period	3	8.9718**	5.2594	8.5876**	5.1401

Note: The first period is from 2 Jan 2004 to 12 Mar 2004, the second period is from 15 Mar 2004 to 14 May 2004, and the third period is from 17 May 2004 to 11 June 2004. The relevant critical value bounds are 4.94–5.73 at the 95% significance level and 6.84–7.84 at the 99% significance level. Single and double asterisks indicate that the F-statistic falls above the 95 and 99%upper bound. The unrestricted error correction (UEC) regressions are:

$$\Delta S = \beta_{S0} + \sum_{i=1}^{n} \beta_{Si} \Delta S_{t-i} + \sum_{j=0}^{n} \alpha_{Sj} \Delta F + \varepsilon_{St}$$

$$\Delta F = \beta_{F0} + \sum_{i=1}^{n} \beta_{Fi} \Delta F_{t-i} + \sum_{j=0}^{n} \alpha_{Fj} \Delta S + \varepsilon_{Ft}$$

where S is TAIEX and F is TX or MTX

between spot and futures are bi-direction, however, in this study, we can clearly indicate whether ought to be the dependent variable.

In the second stage, the Akaike Information Criterion (AIC) is used to estimate Eq. 3. Both spot and futures prices are formulating an ARDL model respectively and the estimates are reported in Table 3.

As expected, such modeling framework provides well efficient estimates of parameters and all the diagnostic testing are statistically insignificant implying no evidence of misspecification. The adjusted R square is very large in the first and third period that means the futures market can powerfully explain the spot market. The computed F-statistics clearly reject the null hypothesis that all regressors have zero coefficients for all cases, suggesting that such ARDL models fit the data reasonably well. The dependent variable TAIEX follow ARDL(3,3) process under the first and the second period. The current coefficient of futures is positive and the other three lagged ones are negative.

In contrast, during the second period, the adjusted R square is very low when the futures price, TX, is chosen as dependent variable. The model follows ARDL (1,0) process at 99% significant level. This result demonstrates that the first lagged prices of TAIEX affect the current prices of TX, however, only the current prices of TAIEX influence the prices of TX. The case of MTX is similar. Overall, in this period it is suggested that the ability of price discovery does not exist for both TX and MTX.

On the other hand, the second period almost covers the duration between the presidential election and presidential inauguration. After a bitter campaign and an assassination attempt, the Taiwan President campaign in 2004 is keen. The winning party won by a mere 29,518 votes (0.2% margin). Such result soundly aggravated internal discord with respect to social consciousness in Taiwan. The opposite party demonstrates for fair election trial and such political turbulent has continued till June after the day of presidential inauguration. Carfinkel et al. (1999) provides evidence that the futures price may failed to forecast the spot price

Table 3 Estimates of ARDL model for index and futures market

First period	TAIEX–TX	TAIEX–MTX
	Dependent variable: S	Dependent variable: S
Coefficient	AIC-ARDL(3,3)	AIC-ARDL(3,3)
Constant	0.018378 [2.1836]*	0.018255 [2.1574]*
S_{t-1}	0.60732 [21.3110]**	0.59687 [20.8379]**
S_{t-2}	0.22563 [6.9046]**	0.24023 [7.3441]**
S_{t-3}	0.13136 [4.6525]**	0.12858 [4.5070]**
F	0.90532 [48.8151]**	0.93648 [50.1317]**
F_{t-1}	−0.45484 [−12.3814]**	−0.48977 [−12.7553]**
F_{t-2}	−0.26772 [−6.9518]**	−0.25932 [−6.3858]**
F_{t-3}	−0.14917 [−4.5983]**	−0.15517 [−4.6273]**
$\overline{R}^2$	0.99919	0.99920
F-statistic	213541.9	214882.9
Serial correlation-LM test	1.8357	0.071046
DW-statistic	2.0104	2.0010
Second period	TAIEX–TX	TAIEX–MTX
	Dependent variable: F	Dependent variable: F
Coefficient	AIC-ARDL(1,0)	AIC-ARDL(1,0)
Constant	−1.4100 [−3.0971]**	−2.55090 [−5.1832]**
F_{t-1}	0.23429 [9.7964]**	−0.01171 [−0.4869]
S_t	0.81456 [12.9507]**	1.3014 [20.3819]**
$\overline{R}^2$	0.29686	0.23409
F-statistic	244.4604**	265.2293**
Serial correlation-LM test	0.13532	1.9794
DW-statistic	2.0010	2.0028
Third period	TAIEX–TX	TAIEX–MTX
	Dependent variable: S	Dependent variable: S
Coefficient	AIC-ARDL(3,3)	AIC-ARDL(3,3)
Constant	0.021248 [2.4529]**	0.021226 [2.4648]*
S_{t-1}	0.668680 [29.9525]**	0.66676 [29.8287]**
S_{t-2}	0.218300 [8.2780]**	0.22606 [8.6078]**
S_{t-3}	0.086262 [3.9007]**	0.081282 [3.6822]**
F	0.75013 [60.3452]**	0.75486 [61.1183]**
F_{t-1}	−0.42422 [−17.4657]**	−0.41323 [−17.1542]**
F_{t-2}	−0.21648 [−8.4125]**	−0.24339 [−9.6087]**
F_{t-3}	−0.08511 [−4.0051]**	−0.074781 [−3.5132]**
$\overline{R}^2$	0.99838	0.99840
F-statistic	175296.6**	177563.1**

Table 3 continued

Third period	TAIEX–TX	TAIEX–MTX
	Dependent variable: *S*	Dependent variable: *S*
Coefficient	AIC-ARDL(3,3)	AIC-ARDL(3,3)
Serial correlation-LM test	0.68902	0.81420
DW-statistic	2.0031	2.0005

Note: [ ] denotes t-statistics.* significant at the 95% significance level; ** significant at the 99% significance level. The ARDL models are:

$$S_t = \beta_{S0} + \sum_{i=1}^{m} \beta_{st-i} S_t + \sum_{j=0}^{p} \alpha_{St-j} F_t + \mu_{St}$$

$$F_t = \beta_{F0} + \sum_{i=1}^{m} \beta_{Ft-i} F_t + \sum_{j=0}^{p} \alpha_{Ft-j} F_t + \mu_{Ft}$$

where S is TAIEX and F is TX or MTX

Table 4 Estimated long run effects of ARDL model

First period	TAIEX–TX	TAIEX–MTX
	Dependent variable: *S*	Dependent variable: *S*
Coefficient	AIC-ARDL(3,3)	AIC-ARDL(3,3)
Constant	0.51486 [2.7102]**	0.53192 [2.7076]**
F	0.94100 [43.5180]**	0.93904 [41.9947]**
Second period	TAIEX–TX	TAIEX–MTX
	Dependent variable: *F*	Dependent variable: *F*
Coefficient	AIC-ARDL(1,0)	AIC-ARDL(1,0)
Constant	−2.1542 [−3.1258]**	−2.5213 [−5.2228]**
S	1.2444 [15.7878]**	1.2863 [23.2961]**
Third period	TAIEX–TX	TAIEX–MTX
	Dependent variable: *S*	Dependent variable:*S*
Coefficient	AIC-ARDL(3,3)	S AIC-ARDL(3,3)
Constant	0.79421 [2.9668]**	0.81977 [2.9838]**
F	0.90890 [29.2999]**	0.90593 [28.4556]**

Note: [ ] denotes t-statistics.* significant at the 95% significance level; ** significant at the 99% significance level. The long-run relationships are:

$$S_t = \beta_{S0} + \beta_{St} F_t + \mu_{St}$$
$$F_t = \beta_{F0} + \beta_{Ft} S_t + \mu_{Ft}$$

where S is TAIEX and F is TX or MTX

Table 5 Error correction representation of ARDL model

First period	TAIEX–TX	TAIEX–MTX
	Dependent variable: ΔS_t	Dependent variable: ΔS_t
Coefficient	AIC-ARDL(3,3)	AIC-ARDL(3,3)
Constant	0.018378 [2.1836]*	0.018255 [2.1574]*
ΔS_{t-1}	−0.35699 [−12.3522]**	−0.36881 [−12.7038]**
ΔS_{t-2}	−0.13136 [−4.6525]**	−0.12858 [−4.5070]**
ΔF	0.90532 [48.8151]**	0.93648 [50.1317]**
ΔF_{t-1}	0.41689 [12.9901]**	0.41449 [12.5780]**
ΔF_{t-2}	0.14917 [4.5983]**	0.15517 [4.6273]**
ECM_{t-1}	−0.035694 [−3.7543]**	−0.034319 [−3.6784]**
Second period	TAIEX–TX	TAIEX–MTX
	Dependent variable: ΔF_t	Dependent variable: ΔF_t
Coefficient	AIC-ARDL(1,0)	AIC-ARDL(1,0)
Constant	−1.4100 [−3.0971]**	−2.5509 [−5.1832]**
ΔF_{t-1}	−0.11115 [−4.6528]**	–
ΔS	0.81456 [12.9507]**	1.3014 [20.3819]**
ECM_{t-1}	−0.65456 [−22.5831]**	−1.0117 [−42.0594]**
Third period	TAIEX–TX	TAIEX–MTX
	Dependent variable: ΔS_t	Dependent Variable: ΔS_t
Coefficient	AIC-ARDL(3,3)	AIC-ARDL(3,3)
Constant	0.02124 [2.4529]**	0.021226 [2.4648]*
ΔS_{t-1}	−0.30456 [−13.5385]**	−0.30734 [−13.6397]**
ΔS_{t-2}	−0.08626 [−3.9007]**	−0.081282 [−3.6822]**
ΔF	0.75013 [60.3452]**	0.75486 [61.1183]**
ΔF_{t-1}	0.30159 [14.2990]**	0.31817 [15.0489]**
ΔF_{t-2}	0.08511 [4.0051]**	0.074781 [3.5132]**
ECM_{t-1}	−.026754 [−4.3981]**	−0.025892 [−4.2912]**

Note: [ ] denotes t-statistics.* significant at the 95% significance level; ** significant at the 99% significance level. The error correction representation of ARDL models are:

$$\Delta S_t = \beta_{S0} + \sum_{i=1}^{m-1} \beta_{Si} \Delta S_{t-i} + \sum_{i=0}^{p-1} \alpha_{Fi} \Delta F_{t-i} - \gamma_S ECM_{St-1} + \varepsilon_{St};\ ECM_{St-1} = S_{t-1} - \beta_{S0} - \beta_{St} F_t$$

$$\Delta F_t = \beta_{F0} + \sum_{i=1}^{m-1} \beta_{Fi} \Delta F_{t-i} + \sum_{i=0}^{p-1} \alpha_{Si} \Delta S_{t-i} - \gamma_F ECM_{Ft-1} + \varepsilon_{Ft};\ ECM_{Ft-1} = F_{t-1} - \beta_{F0} - \beta_{Ft} S_t$$

where S is TAIEX and F is TX or MTX

during such circumstance which called the phenomenon of ‘surprising election outcomes’. Our result is substantially consistent with their findings.

Table 4 shows the long-run equilibrium relationship between spot and futures market. Especially, for the dependent variable, TAIEX, both the coefficients of TX and MTX are almost 1.

The rationale behind the concept of cointegration is that there exists a long-run equilibrium relationship between the two variables. In the short-run, they may deviate from each other but market forces will bring them back together. Table 5 shows that during the first and third period, the speed of adjustment coefficient is significant that means that the futures market is leading the spot market. The first two lags of the futures innovations are statistically significant, indicating that the futures market leads the spot market by at least 20 min.

During the second period, the speed of adjustment coefficient is significant. It means that the spot market has a long-run equilibrium relationship with the futures market. However, there is no any spot innovations are statistically significant, indicating that the spot market mere simultaneous reacts new information with the futures market.

4 Conclusion

In this article, we study the price discovery role of futures prices on the Taiwan stock index. The major findings are as follows. First, spot and futures prices stand in a long-run relationship between them; hence, an ARDL-ECM method can be used to investigate the short-run dynamics and the price movements in the two markets. Second, the ARDL bound tests indicate that there is a stable and unique unidirectional lead-lag effect which confirms that futures prices tend to discover new information rather than spot prices. This pattern is thought to reflect the fundamentals of the underlying asset since, due to the limitations of short-selling the spot index, investors who have collected and analyzed new information would prefer to trade in the futures rather than in the spot market. Third, results during the second period which is between presidential election and presidential inauguration reveal that future market has no predictive power on spot market. Such interesting finding is consistent with the effect of ‘surprising election outcomes’ (Carfinkel et al. 1999). Finally, information from the futures prices can be used to generate more accurate forecasts of the spot prices but not the other way round. This reflects that stronger causality from futures to spot runs and that most of the variability in the futures returns is attributed to pure innovations which cannot be predicted.

Thus, there are the following implications. First, it seems that incestora can benefit by efficiently using the information contained in futures prices. For instance, market agents can use futures prices to generate more accurate forecasts of the spot price index; as a result, they can design more efficient investment and speculative trading strategies. Second, the causal relationship may help regulators to indicate which of the two markets is most likely to be used by informed traders. Regulators attempting to detect the presence of traders using price-sensitive information, which is illegally, will wish to know the most likely market for these informed traders, and whether the market structure allows or impedes this detection. Our research appears that the index future markets may needs more consideration for regulation purpose rather than spot markets. Moreover, the least 30 min lag systematic response between futures and spot markets has provided available arbitrage opportunities for investors.

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