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Asymmetric price transmission within the Argentinean stock market: an asymmetric threshold cointegration approach

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Abstract This study uses the threshold cointegration and asymmetric error correction models to examine the long-run asymmetric equilibrium relationships between individual prices and the general stock index in the Argentinean stock market. We find that only five shares become cointegrated with the general national stock index and show signs of asymmetric adjustment. Besides, unlike ALUA and GGAL shares, the threshold cointegration analysis reveals that, in the long-term, the BMA, EDN and APBR shares have a much faster reaction to negative deviations from long-term equilibrium than positive deviations. Furthermore, the error correction model discloses that, in the short-term, the adjustment speed of EDN-share is faster when the deviation from the long-run equilibrium is positive than when it is negative. Besides, it is found that the ALUA, BMA, GGAL and APBR shares have a much slower reaction to positive deviations from long-term equilibrium than negative deviations. Finally, a pairs trading rule, based on the estimated threshold cointegration model, shows the usefulness of our findings as it generates a significantly higher return than a naive buy-and-hold trading rule.

Keywords Asymmetric price transmission · Threshold cointegration · Structural change · Asymmetric adjustment · Asymmetric error correction · Causality · Pairs trading rule

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1 Introduction

The stock markets are broadly characterized by movements in their share prices that naturally depend on a number of exogenous and endogenous factors. According to Menezes et al. (2004), these movements may be upwards or downwards in response to changes in the predictors. Nevertheless, the magnitude of positive and negative responses may differ for similar positive and negative variations in the predictors, in which case the variables display asymmetric adjustment over the business cycle (see Menezes et al. 2004).

Cointegration and causality analyses are broadly used to investigate the interdependence and the long-run cointegration relationships among stock markets (see Taylor and Tonks 1989; Liu et al. 1997; Laurence et al. 1997; Su and Fleisher 1997; Huang et al. 2000; Ansotegui and Esteban 2002; Fernandez-Serrano and Sosvilla-Rivero 2003). Studies using firm level shares, rather than stock indexes, are also available in the literature (see Chan et al. 2001; Menezes et al. 2004; Shen et al. 2007). The standard cointegration test of Engle and Granger (1987) assumes that the adjustment mechanism of the error correction term is symmetric. This indicates that the adjustment coefficients are the same no matter if the equilibrium error is positive or negative. That is, the adjustment speed of stock prices is the same regardless of the kind of shocks. Nevertheless, recent empirical studies, using positive and negative error terms to denote the positive returns (good news) and negative returns (bad news), have found that the adjustment speed of stock prices is slower for positive shocks than for negative ones (see Li and Lam 1995; Koutmos 1998; Chiang 2001; Sarantis 2001; Shen et al. 2007).

In this paper, we provide support for asymmetric adjustment behavior in Argentinean stocks, using the threshold autoregressive class models. Moreover, we take into account the long-run relationship between the prices in the Argentinean stock market. To do so, we use the Enders and Siklos (2001) asymmetric cointegration model to analyze the long-run asymmetric equilibrium relationship between the Argentinean stock prices. To be specific, the adjustment coefficient of the error correction term is different when the equilibrium error is positive from when it is negative.

This study contributes to the literature by helping us better understand the information transmission mechanisms between the Argentinean stock prices and by providing investors with a useful reference when making decision about investment portfolio. Given the features of the Argentinean stock market, one would expect a relatively high elasticity of supply and low asymmetry of price transmission in the relationship between the general national stock index (MERVAL) and individual stock market prices. The MERVAL-index is used as a proxy to represent the weighted overall performance of the Argentinean stock market. Finally, using the estimated threshold cointegration model, we develop a pairs trading rule which could generate a higher return than a naive buy-and-hold rule.

Pairs trading approach is a statistical arbitrage hedge fund strategy designed to exploit short-term deviations from a long-run equilibrium pricing relationship between two stocks (see Lin et al. 2006). Traditional methods of pairs trading have sought to identify trading pairs based on correlation and other nonparametric decision rules. However, these approaches do not guarantee the single most important statistical property which is fundamental to a profitable pairs trading strategy, namely mean reversion (see Lin et al. 2006). This study selects trading pairs based on the presence of a threshold cointegrating relationship between two stock price series. If two cointegrated stocks share a long-run equilibrium relationship, then deviations from this equilibrium are only short-term and are expected to return to zero in future periods.

As compared to the classical but rather limited concept of correlation, as a measure of co-dependency, the main advantage of cointegration analysis is that it enables the use of the entire information set comprised in the levels of financial variables (see Engle and Granger 1987; Johansen 1988). Furthermore, a cointegrating relationship is able to explain the long-run behavior of cointegrated series, whereas correlation usually lacks stability, being only a short-run measure. The enhanced stability of a cointegrating relationship generates a number of significant advantages for a trading strategy. These include the reduction of the amount of rebalancing of trades in a hedging strategy and, consequently, the associated transaction costs (see Huck and Afawubo 2014).

The concept of cointegration has been used in the pairs trading context by Vidyamurthy (2004), Lin et al. (2006), Galenko et al. (2012), Huck and Afawubo (2014), Chiu and Wong (2015), and Chen and Zhu (2015). It shares connection with the frequency of historical reversal in the price spread (see Do and Faff 2010). Cointegration incorporates the idea of mean reversion between stock prices (see Huck and Afawubo 2014; Chiu and Wong 2015). When applied to stock prices and stock market indices, cointegration requires the existence of at least one stationary linear combination between them. A stationary linear combination of stock prices/market indexes can be interpreted as mean reversion in price spreads. The result that the spread in a system of prices is mean reverting does not provide any information for forecasting the individual prices in the system, or the position of the system at some point in the future. However, it does provide the valuable information that the prices in the system will evolve together over the long-term.

If two stock prices or two stock market indices are cointegrated, then a combination of these may be formed such that their spread is stationary, or mean reverting. This means that these stocks share a long-term equilibrium relationship. Pairs trading will try to exploit deviations from an equilibrium asset-pricing framework with nonstationary common factors (see Bossaerts and Green 1989; Chen and Knez 1995). The application of the cointegration concept to stock price analysis is that a system of nonstationary stock prices in level form can share common stochastic trends (see Stock and Watson 1988). According to Gatev et al. (2006), if the long and short components fluctuate with common nonstationary factors, then the prices of the component portfolios would be cointegrated and the pairs trading strategy would be expected to work.

Our study is motivated by three main reasons. First, Argentina is one of the largest countries within the Latin American region and the universe of emerging countries. With the embankment of market-oriented policies and financial reforms, it is becoming an attractive destination for international capital flows (see Jawadi et al. 2010). Second, none of the empirical studies examined asymmetric price transmission within stock markets. Third, pairs trading rule is developed based on the results of the asymmetric threshold cointegration approach rather than on the standard linear cointegration one.

This paper is organized as follows. Section 2 discusses the econometric methodology. Section 3 presents the empirical findings. Section 4 presents the pairs trading rule, and Sect. 5 concludes the paper.

2 Econometric framework

Cointegration has been widely used to investigate relationship between price variables. The two major cointegration methods are Johansen and Engle–Granger two-step approaches. Both of them assume symmetric relationship between variables. In recent years, threshold cointegration has been increasingly used in price transmission studies. Balke and Fomby (1997) propose a two-step approach for examining threshold cointegration on the basis of the approach developed by Engle and Granger (1987). Enders and Granger (1998) and Enders and Siklos (2001) further generalize the standard Dickey–Fuller test by allowing for the possibility of asymmetric movements in time-series data. This makes it possible to test for cointegration without maintaining the assumption of a symmetric adjustment to a long-term equilibrium. Thereafter, the method has been widely applied to analyze asymmetric price transmission.

Few representative studies investigate the issue of the asymmetric price transmission within stock markets. They include those of Menezes et al. (2004) and Shen et al. (2007). In this study, linear cointegration, threshold cointegration, and asymmetric error correction models are employed to examine the price dynamics in the Argentinean stock market. These models will be able to assess asymmetric price dynamics in the stock market in both the long-term and short-term.

2.1 The cointegration approach

Econometric literature proposes different methodological alternatives to empirically analyze the long-run relationships and dynamics interactions between two or more time-series variables. The most widely used methods include the two-step procedure of Engle and Granger (1987) and the full information maximum likelihood-based approach due to Johansen (1988) and Johansen and Juselius (1990).

The first step of the analysis consists in determining a break point into the (see Engle and Granger 1987) relationship that defines the long-run relationship between the individual price and global stock index price in the Argentinean stock market:

$$Y_{1t} = \xi_0 + \xi_1 Y_{2t} + \varepsilon_t \tag{1}$$

where Y_{1t} and Y_{2t} denote the individual stock price and the MERVAL stock price index in the Argentinean stock market, respectively; ξ_0 and ξ_1 are parameters to be estimated, and ε_t is the disturbance term, which should be stationary if any long-run relationship exists between the two integrated price series.

The parameter ξ_1 indicates the long-run elasticity of price transmission and gives the magnitude of adjustment of the individual stock price to variations of the global stock index. If $\xi_1 < 1$, changes in the global stock index are not fully passed onto the individual stock price. Stock (1987) shows that if variables Y_{1t} and Y_{2t} are cointegrated, then the OLS estimates of ξ_0 and ξ_1 are super-consistent, and the speed of convergence is faster than that of stationary variables.

Residual-based cointegration tests (see Engle and Granger 1987) assume that cointegrating vectors are constant over time. Nevertheless, if there is a regime shift in the series, there will be a shift in the cointegrating vector as well. In such circumstances, these standard tests could lead to incorrect inferences about the long-run relationship of the price series. Moreover, Phillips (1986) shows that if a structural break exists in the data, but is omitted from the cointegration relationship, this could lead to spurious rejections when the null of no cointegration is wrongly rejected. For the Engle and Granger (1987) test, such spurious rejections tend to occur for breaks that are located either too early in the sample or when the magnitude of the break increases. Thus, the power of the Engle and Granger (1987) test to find cointegration is severely affected by the presence of breaks in the level or the trend function in the cointegration relationship.

Gregory and Hansen (1996a, 1996b) addressed this issue and proposed a residual-based cointegration test that allows for the possibility of regime shifts either in the intercept or the entire vector of coefficients. Gregory and Hansen (1996a, 1996b) analyzed four models and then tested the null hypothesis of no cointegration. Model 1(see Eq. 1) is the standard cointegration model where no changes in the intercept or a trend function are allowed under the null hypothesis. The other three models include shifts in either the intercept (Level shift model C) or trend (Level shift model with trend C/T) or shifts in the intercept and slope vector of coefficients (Regime shift model C/S). Model C/S is unique in the sense it allows the long-run equilibrium relationship to rotate as well as shift in parallel fashion. The break point τ in any model is determined endogenously within the data series.

Level shift model C can be expressed as follows:

$$Y_{1t} = \xi_0' + \xi_0'' \phi_{tt_0} + \xi_1 Y_{2t} + \epsilon_t \tag{2}$$

In this parameterization, ξ_0' represents the intercept before the shift, and ξ_0'' denotes the change in the intercept at the time of the shift.

Level shift model with trend C/T can be represented by:

$$Y_{1t} = \xi_0' + \xi_0'' \phi_{tt_0} + \beta t + \xi_1 Y_{2t} + \upsilon_t \tag{3}$$

Regime shift model C/S is given as:

$$Y_{1t} = \xi_0' + \xi_0'' \phi_{tt_0} + \xi_1' Y_{2t} + \xi_1'' Y_{2t} \phi_{tt_0} + \kappa_t \tag{4}$$

In this case, ξ_0' and ξ_0'' are as in the level shift model C. ξ_1' denotes the cointegrating slope coefficients before the regime shift, and ξ_1'' denotes the change in the slope coefficients.

A time trend into the regime shift model $(C/S/T)$ could be also introduced:

$$Y_{1t} = \xi_0' + \xi_0'' \phi_{tt_0} + \beta t + \xi_1' Y_{2t} + \xi_1'' Y_{2t} \phi_{tt_0} + \eta_t \tag{5}$$

In these four models above, the structural break is modeled by the introduction of a dummy variable ϕ_{tt_0}, which takes values (0, 1) depending on the nature of the structural break.

$$\phi_{t\tau} = \begin{cases} 1 & \text{if} \quad t > t_0 \\ 0 & \text{if} \quad t \leq t_0 \end{cases} \tag{6}$$

where t_0 is the unknown parameter denoting the timing of the change point.

In all four models postulated, the null hypothesis of no cointegration can be tested by examining whether the residuals of the ordinary least-squares (OLS) regression applied to Eqs. (1) and (2)–(5), respectively, are stationary processes.

The procedure for computing the test statistic for each possible regime shift $t_0 \in T$ involves four steps. In essence, it involves the search for the smallest value of either the modified Phillips–Perron (PP) (Z_ξ^* and Z_t^*) or ADF(ADF*) test statistic across all possible break points:

$$Z_\xi^* = \inf_{t_0 \in T} Z_\xi(t_0) \tag{7}$$

$$Z_t^* = \inf_{t_0 \in T} Z_t(t_0) \tag{8}$$

$$\text{ADF}^* = \inf_{t_0 \in T} ADF(t_0) \tag{9}$$

2.2 Modeling asymmetries in price transmission within a cointegration framework

The standard approach of Engle and Granger (1987) assumes that ε_t from Eq. (1) behaves as an autoregressive process in the form of:

$$\Delta\varepsilon_t = \rho\varepsilon_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta\varepsilon_{t-i} + z_t \tag{10}$$

where ρ measures the speed of convergence of the system, z_t is a white-noise disturbance and the residuals from the regression model are used to estimate $\Delta\varepsilon_t$.

Rejecting the null hypothesis of no cointegration $\rho = 0$ in favor of the alternative hypothesis $-2 < \rho < 0$ implies that the $\{\varepsilon_t\}$ sequence is stationary with mean zero. Any deviations from the long-run value of the disturbance term ε_t are ultimately eliminated. Convergence is assured if $-2 < \rho < 0$. As such, Eq. (1) is an attractor such that ε_t can be written as an error correction model. The change in ε_t equals ρ multiplied by ε_{t-1} regardless of whether $\varepsilon_{t-1} \geq 0$ or $\varepsilon_{t-1} < 0$.

Nevertheless, the implicit assumption of linear and symmetric adjustment is problematic. Enders and Siklos (2001) argue that the Engle–Granger cointegration test is likely to lead to misspecification errors when the adjustment of the error correction term is asymmetric. They remedy this error by expanding the Engle–Granger two-step cointegration test to incorporate an asymmetric error correction term. In the third step, we determine whether or not the disturbance term ε_t is stationary by considering an asymmetric test methodology in the form of threshold autoregressive (TAR) cointegration model as proposed by Enders and Granger (1998) and Enders and Siklos (2001):

$$\Delta\varepsilon_t = I_t\rho_1(\varepsilon_{t-1} - \tau) + (1 - I_t)\rho_2(\varepsilon_{t-1} - \tau) + \mu_t \tag{11}$$

where ρ_1, ρ_2 are coefficients, τ is the value of the threshold, μ_t is a white-noise disturbance and I_t is the Heaviside indicator such that

$$I_t = \begin{cases} 1 & \text{if} \quad \varepsilon_{t-1} \geq \tau \\ 0 & \text{if} \quad \varepsilon_{t-1} < \tau \end{cases} \tag{12}$$

In order for $\{\varepsilon_t\}$ to be stationary, a necessary condition is $-2 < (\rho_1, \rho_2) < 0$. If the variance of μ_t is sufficiently large, it is also possible for one value of ρ_j to be in the range of -2 and 0 and for the other value to equal zero. Although there is no convergence in the regime with the unit root (i.e., the regime in which $\rho_j = 0$), large realizations of μ_t will switch the system into the convergent regime.

In both cases, under the null assumption of no cointegration between the variables, the F-statistic for the null hypothesis $\rho_1 = \rho_2 = 0$ has a nonstandard distribution. Rejecting this assumption means that Eq. (3) is an attractor such that the equilibrium value of the $\{\varepsilon_t\}$ is τ. The adjustment process is $\rho_1(\varepsilon_{t-1} - \tau)$ if the lagged value of ε_t is above its long-run equilibrium value, while if the lagged value of ε_t is below its long-run equilibrium value, the adjustment is $\rho_2(\varepsilon_{t-1} - \tau)$. If $-1 < |\rho_1| < |\rho_2| < 0$, negative discrepancies will be more persistent than positive discrepancies. Moreover, Tong (1983) showed that the OLS estimates of ρ_1 and ρ_2 have an asymptotic multivariate normal distribution if the sequence $\{\varepsilon_t\}$ is stationary. Therefore, if the null assumption $\rho_1 = \rho_2 = 0$ is rejected, it is possible to test for symmetric adjustment (i.e., $\rho_1 = \rho_2$) using a standard F-test. Since adjustment is symmetric if $\rho_1 = \rho_2$, the Engle–Granger cointegration test is a special case of Eq. (3). Rejecting both the null assumptions $\rho_1 = \rho_2 = 0$ and $\rho_1 = \rho_2$ indicates the existence of threshold cointegration and asymmetric adjustment.

Since the exact nature of the nonlinearity may not be known, Enders and Siklos (2001) consider another kind of asymmetric cointegration test methodology that allows the adjustment to be contingent on the change in ε_{t-1} (i.e., $\Delta\varepsilon_{t-1}$) instead of the level of ε_{t-1}. In this case, the Heaviside indicator of Eq. (12) becomes

$$I_t = \begin{cases} 1 & \text{if} \quad \Delta\varepsilon_{t-1} \geq \tau \\ 0 & \text{if} \quad \Delta\varepsilon_{t-1} < \tau \end{cases} \tag{13}$$

Enders and Granger (1998), Enders and Siklos (2001), Kuo and Enders (2004) and Thompson (2006), among others, argue that this specification is especially relevant when the adjustment is such that the series exhibits more 'momentum' in one direction than in the other. That is, the speed of adjustment depends on whether ε_t is increasing (i.e., widening) or decreasing (i.e., narrowing). According to Thompson (2006), among others, if $|\rho_1| < |\rho_2|$, then increase in ε_t tends to persist, whereas decreases revert back to the threshold quickly. The resulting model is called momentum-threshold autoregressive (M-TAR) cointegration model. The TAR model captures asymmetrically deep movements if, for instance, positive deviations are more prolonged than negative deviations. The M-TAR model allows the autoregressive decay to depend on $\Delta\varepsilon_{t-1}$. As such, the M-TAR specification can capture asymmetrically 'sharp' movements in $\{\varepsilon_t\}$ sequence (see Caner and Hansen 2001).

In both the TAR and M-TAR cointegration processes, the null assumption of $\rho_1 = \rho_2 = 0$ could be tested, while the null hypothesis of symmetric adjustment may be tested by the restriction, $\rho_1 = \rho_2$. Generally, there is no presumption to whether to use TAR or M-TAR specifications. Thus, it is recommended to select the adjustment mechanism by a model selection criterion such as AIC or SBC. Furthermore, if the errors in Eq. (11) are serially correlated, it is possible to use the augmented form of the test:

$$\Delta\varepsilon_t = I_t\rho_1\left(\varepsilon_{t-1} - \tau\right) + (1 - I_t)\,\rho_2\left(\varepsilon_{t-1} - \tau\right) + \sum_{i=1}^{p}\delta_i\Delta\varepsilon_{t-i} + v_t \tag{14}$$

To use the tests, we first regress ε_t on a constant and call the residuals $\{\hat{\varepsilon}_t\}$, which are the estimates of $(\varepsilon_{t-1} - \tau)$. In a second step, we set the indicator according to Eqs. (12) or (13) and estimate the following regression:

$$\Delta\hat{\varepsilon}_t = I_t\rho_1\left(\hat{\varepsilon}_{t-1} - \tau\right) + (1 - I_t)\,\rho_2(\hat{\varepsilon}_{t-1} - \tau) + \sum_{i=1}^{p}\delta_i\Delta\hat{\varepsilon}_{t-i} + v_t \tag{15}$$

The number of lags p is specified to account serially correlated residuals, and it can be selected using AIC, BIC, or Ljung–Box Q test. In several applications, there is no reason to expect the threshold to correspond with the attractor (i.e., $\tau = 0$). In such circumstances, it is necessary to estimate the value of τ along with the values of ρ_1 and ρ_2. A consistent estimate of the threshold τ can be obtained by adopting the methodology of Chan (1993). A super-consistent estimate of the threshold value can be attained with several steps. First, the process involves sorting in ascending order the threshold variable, i.e., $\hat{\varepsilon}_{t-1}$ for the TAR model or the $\Delta\hat{\varepsilon}_{t-1}$ for the M-TAR model. Second, the potential threshold values are determined. If the threshold value is to be meaningful, the threshold variable must actually cross the threshold value (see Enders 2004). Thus, the threshold value τ should lie between the maximum and minimum values of the threshold variable.

In practice, the highest and lowest 15 % of the values were removed from the search to ensure an adequate number of observations on each side. The middle 70 % values of the sorted threshold variable are used as potential threshold values. Third, the TAR or M-TAR model is estimated with each potential threshold value. The sum of squared errors for each trial can be calculated and the relationship between the sum of squared errors and the threshold value can be examined. Finally, the threshold value yielding the lowest sum of squared errors is deemed to be the consistent estimate of the threshold.

Given these considerations, a total of four models are used in this study. They are TAR—Eq. (12) with $\tau = 0$; consistent TAR—Eq. (12) with τ estimated; M-TAR—Eq. (13) with $\tau = 0$; and consistent M-TAR—Eq. (13) with τ estimated. Since there is generally no presumption on which specification is used, it is recommended to choose the appropriate adjustment mechanism via model selection criteria of AIC and BIC (see Enders and Siklos 2001). A model with the lowest AIC and BIC will be used for further analysis.

Insights into the asymmetric adjustments in the context of a long-term cointegration relationship can be obtained with two tests. First, an F-test is used to examine the null assumption of no cointegration ($\mathrm{H}_0 : \rho_1 = \rho_2 = 0$)[1] against the alternative of cointegration with either TAR or M-TAR threshold adjustment. Let Φ and Φ^* denote the F-statistics for testing the null assumption of $\rho_1 = \rho_2 = 0$ under the TAR and the M-TAR specifications, respectively. The distributions of Φ and Φ^* are determined by the form of the attractor. The second one is a standard F-test to assess the null assumption of symmetric adjustment in the long-term equilibrium ($\mathrm{H}_0 : \rho_1 = \rho_2$). Rejection of the null hypothesis indicates the existence of an asymmetric adjustment process.

2.3 Asymmetric error correction model with threshold cointegration

The equilibrium correction specification (ECM) of Engle and Granger (1987) assumes that the adjustment process due to disequilibrium among the variables is symmetric. In order to incorporate asymmetries, two extensions on the ECM model have been made. Error correction terms and first differences on the variables are decomposed into positive and negative values, as proposed by Granger and Lee (1989). The second extension adds the threshold cointegration mechanism to the Granger and Lee (1989) approach. The resulting asymmetric error correction model with threshold cointegration has the form:

$$\begin{aligned}\Delta Y_{kt} = \theta_k + \delta_k^+ Z_{t-1}^+ + \delta_k^- Z_{t-1}^- + \sum_{j=1}^{J} \alpha_{kj}^+ \Delta Y_{1,t-j}^+ + \sum_{j=1}^{J} \alpha_{kj}^- \Delta Y_{1,t-j}^- \\ + \sum_{j=1}^{J} \beta_{kj}^+ \Delta Y_{2,t-j}^+ + \sum_{j=1}^{J} \beta_{kj}^- \Delta Y_{2,t-j}^- + \nu_{kt}\end{aligned} \tag{16}$$

where $k = \{1, 2\}$, $Z_{t-1}^+ = I_t \hat{\varepsilon}_{t-1}$ and $Z_{t-1}^- = (1 - I_t)\hat{\varepsilon}_{t-1}$

The Heaviside indicator function is constructed from Eqs. (12) or (14). The superscripts "+" and "−" indicate that the variables are split into positive and negative components. The first differences are defined as

[1] The null hypothesis of non stationarity is rejected if the sample value of F test statistic exceeds the Enders–Granger critical value. The critical values of the F-statistics for the null hypothesis $\rho_1 = \rho_2 = 0$ using the TAR and M-TAR specifications are reported in the first and second panels of Table 1 in Kuo and Enders (2004).

$$\Delta Y_{k,t-i}^{+} = \max\left\{\Delta Y_{k,t-i}, 0\right\} \tag{17}$$

$$\Delta Y_{k,t-i}^{-} = \min\left\{\Delta Y_{k,t-i}, 0\right\} \tag{18}$$

The lag J is specified to account serially correlated residuals and is selected using AIC statistic and Ljung–Box Q test. The above specification is able to distinguish between long-run and short-run adjustments of $Y_{k,t}$. The long-run adjustment is determined by the parameters $\delta_k^{+}$and δ_k^{-}, whereas the short-run adjustment is governed by the parameters $\alpha_{kj}^{+}, \alpha_{kj}^{-}, \beta_{kj}^{+}$ and β_{kj}^{-} for $j = 1, \ldots, J$ and $k = \{1, 2\}$. If $\delta_k^{+} \neq \delta_k^{-}$, $Y_{k,t}$ exhibits asymmetry in long-run adjustment. If either $\alpha_{kj}^{+} \neq \alpha_{kj}^{-}$ or $\beta_{kj}^{+} \neq \beta_{kj}^{-}$ or both, $Y_{k,t}$ displays asymmetry in short-run adjustment.

In this paper, four types of single or joint null hypotheses and F-tests are examined (see Meyer and Von Cramon-Taubade 2004; Frey and Manera 2007; Sun 2011). The first type is the Granger causality test to examine the lead–lag relationship between $Y_{1,t}$ and $Y_{2,t}$. The null hypothesis that $Y_{1,t}$ does not lead $Y_{2,t}$ can be tested by restricting $H_{01} : \alpha_{2j}^{+} = \alpha_{2j}^{-} = 0$ for all lags j simultaneously and then employing an F-test. Similarly, the null hypothesis that $Y_{2,t}$ does not lead $Y_{1,t}$ can be tested by restricting $H_{02} : \beta_{1j}^{+} = \beta_{1j}^{-} = 0$ for all lags j simultaneously and then employing an F-test. The second type of hypothesis is concerned with the *distributed lag asymmetric effect* on its own variable $Y_{k,t}$; that is, $H_{03} : \alpha_{1j}^{+} = \alpha_{1j}^{-} = 0$ and $H_{04} : \beta_{2j}^{+} = \beta_{2j}^{-} = 0$. The third type of null hypothesis is the *cumulative symmetric effect* which can be expressed as $H_{05} : \sum_{j=1}^{J} \alpha_{1j}^{+} = \sum_{j=1}^{J} \alpha_{1j}^{-}$ for $Y_{1,t}$ and $H_{06} : \sum_{j=1}^{J} \beta_{2j}^{+} = \sum_{j=1}^{J} \beta_{2j}^{-}$ for $Y_{2,t}$. Finally, the *equilibrium adjustment path asymmetry* can be examined with the null hypothesis of $H_{07} : \delta_k^{+} = \delta_k^{-}$ to examine whether it is possible to get back to equilibrium after a shock, and if it is the case, how long it will take.

3 Empirical results

3.1 Summary statistics

This paper focuses on weekly closing values of the general MERVAL stock Index and individual stock market prices[2] for the Argentinean Stock market. The general stock market index is used as a proxy to represent the weighted overall performance of the national stock market. The sample period runs from April 30, 2007 to October 13, 2014, with a total of 390 weekly observations obtained for each variable. Table 1 lists all the variables used in this study. All price series are transformed into natural logarithms.

Table 2 shows the descriptive statistics of the stock prices returns. The average daily return of GGAL-share is 43.9 % and is higher than the other values in the Argentinean stock market. The highest standard deviation is observed for the TS-share return (20.829). The high volatilities of stock prices shall not be surprising since this is the typical pattern in emerging markets, and the Argentinean stock market is no exception.

[2] Data are collected from the Yahoo Finance website www.yahoo.finances.fr.

Table 1 Components of the MERVAL stock index

Symbol	Title
ALUA.BA	Aluar Aluminio Argentino S.A.I.C.
APBR.BA	Petr
BMA.BA	Banco Macro S.A.
COME.BA	Sociedad Comercial del Plata S.A.
EDN.BA	EMP.DIST.Y COM.NORTE
ERAR.BA	Ternium Siderar
FRAN.BA	BBVA Banco Franc
GGAL.BA	Grupo Financiero Galicia S.A.
PAMP.BA	Pampa Energia SA
PESA.BA	Petrobras Argentina SA
TECO2.BA	Telecom Argentina S.A.
TS.BA	Tenaris SA
YPFD.BA	YPF S.A.

The Ljung–Box Q statistics for ALUA, BMA, APBR and YPFD shares are indicative of a strong autocorrelation, respectively.

Table 3 lists the paired correlation coefficients between the stock return series in the Argentinean stock market. The majority of the shares are highly correlated with MERVAL-index in the Argentinean stock market. The correlation coefficients between these series indicate a close relationship between Argentinean stock returns.

Figure 1 plots the share prices of the Argentinean stock market. A clear comovement between share prices and MERVAL stock price index is evident. In contrast, some shares seem to comove for some periods but also display divergent movement regardless of the market. This time-varying comovement may not be detected when the standard linear cointegration model is used, implying that there is a need to try nonlinear cointegration (see Balke and Fomby 1997; Siklos and Granger 1997).

3.2 Results of the unit root test

Before the cointegration analysis, we first examine whether each of the equity prices and MERVAL stock price index is an I(1) process or not. We apply the Augmented Dickey–Fuller (ADF) test on each individual price series (in logarithms). Results are given in Table 4. Three different models are considered: model without constant, nor deterministic trend, model with constant, without deterministic trend and model with constant and deterministic trend. All series are I(1) at the 1 % significance level or better.

3.3 Results of the linear cointegration analysis

Table 5 reports the estimated coefficients (ξ_0 and ξ_1) of the cointegrating vector for each series. We find that the estimated coefficients of the cointegrating vector are all statistically significant at the 1 or 5 % levels.

Table 2 Summary statistics for the returns of Argentinean's stock prices

	Mean	SD	Skewness		Excess Kurtosis		J–B		L–B $Q(20)$	
			Value	p value	Value	p value	Value	p value	Value	p value
ALUA	0.149	5.614	−0.158	0.202	3.456***	0.000	195.248***	0.000	39.328***	0.006
BMA	0.363	8.125	−0.075	0.545	13.454***	0.000	2934.413***	0.000	36.745**	0.013
FRAN	0.359	7.366	−0.415***	0.001	5.944***	0.000	583.755***	0.000	27.172	0.130
EDN	0.255	8.253	−0.469***	0.000	6.100***	0.000	617.402***	0.000	21.469	0.370
GGAL	0.439	6.935	−0.672***	0.000	6.782***	0.000	774.883***	0.000	24.614	0.217
MERVAL	0.407	4.881	−0.939***	0.000	6.222***	0.000	684.614***	0.000	20.595	0.421
PAMP	0.182	6.163	−0.127	0.304	3.553***	0.000	205.659***	0.000	17.476	0.622
APBR	0.071	7.633	−2.194***	0.000	18.965***	0.000	6142.046***	0.000	30.749*	0.059
PESA	−0.152	9.221	−9.144***	0.000	136.272***	0.000	306,410.4***	0.000	15.329	0.757
COME	0.326	8.221	0.659***	0.000	4.456***	0.000	349.954***	0.000	10.508	0.958
TECO2	0.348	6.850	−1.587***	0.000	17.261***	0.000	4992.344***	0.000	14.756	0.790
TS	−0.603	20.829	−17.204***	0.000	320.964***	0.000	1,688,934***	0.000	0.146	1.000
ERAR	−0.292	14.591	−14.328***	0.000	251.864***	0.000	1,041,490***	0.000	10.480	0.959
YPFD	0.308	6.502	−1.055***	0.000	8.505***	0.000	1244.511***	0.000	32.128**	0.042

The symbols *, ** and *** denote statistical significance at 10, 5 and 1 % levels, respectively. J–B refers to Jarque–Bera statistics and L–B represents Ljung–Box Q statistics

Table 3 Correlation coefficients between Argentinean's stock prices returns

	ALUA	BMA	FRAN	EDN	GGAL	MERVAL	PAMP	APBR	PESA	COME	TECO2	TS	ERAR	YPFD
ALUA	1													
BMA	0.4016	1												
FRAN	0.5387	0.6894	1											
EDN	0.4712	0.4639	0.5877	1										
GGAL	0.5540	0.6752	0.8371	0.5960	1									
MERVAL	0.6897	0.6905	0.8537	0.6449	0.8377	1								
PAMP	0.4675	0.5122	0.6146	0.7171	0.6353	0.6857	1							
APBR	0.4180	0.3269	0.4150	0.2309	0.3872	0.5896	0.2520	1						
PESA	0.2364	0.1554	0.2136	0.2136	0.2473	0.3032	0.2255	0.2271	1					
COME	0.4404	0.3297	0.4082	0.3571	0.4241	0.4968	0.3791	0.2829	0.1770	1				
TECO2	0.5554	0.5909	0.7011	0.4912	0.6656	0.7409	0.5534	0.3801	0.2209	0.3763	1			
TS	0.2496	0.2079	0.2423	0.1171	0.2228	0.3133	0.1442	0.2600	0.1121	0.1858	0.1774	1		
ERAR	0.2660	0.2311	0.2858	0.2369	0.2919	0.3346	0.2155	0.2171	0.1474	0.1311	0.2435	0.0852	1	
YPFD	0.2505	0.2861	0.2925	0.2350	0.2606	0.3966	0.2313	0.1882	0.1688	0.2139	0.2273	0.1231	0.2010	1

The sample period is from April 30, 2007 to October 13, 2014

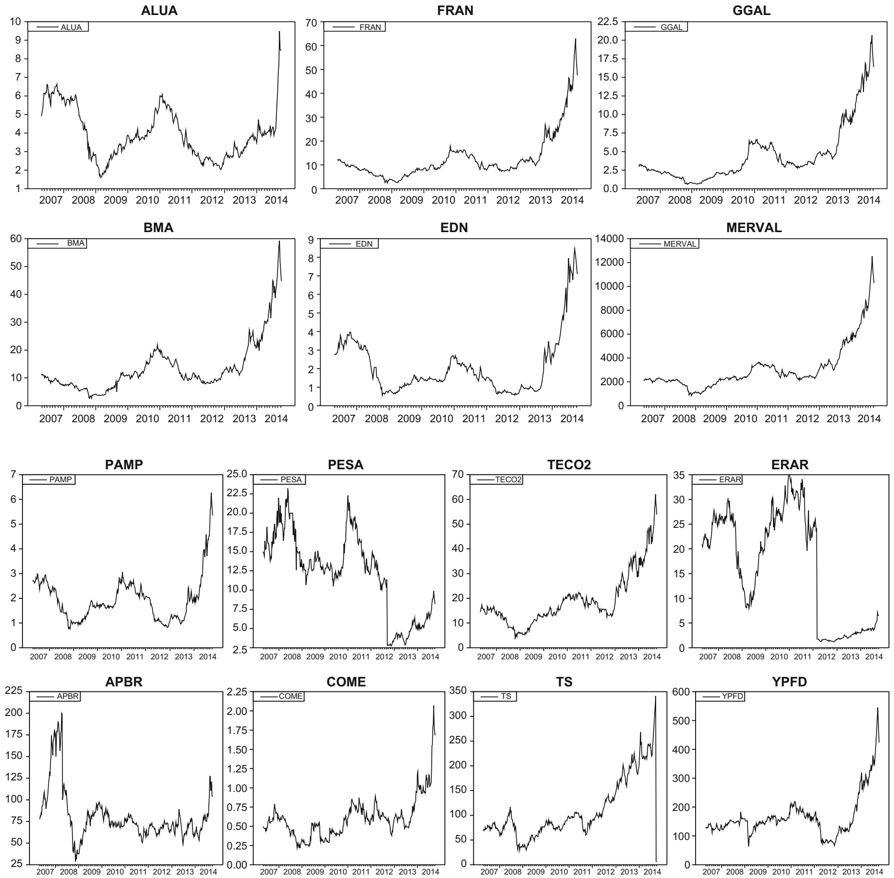

Fig. 1 Plots of the time series of the Argentinean shares and MERVAL stock price index

Table 6 presents the results from the application of the Engle–Granger procedure to Eq. (1) with the lag length selected using the AIC. We include a number of lags enough to remove dependence or serial correlation in the residuals. These test results indicate that the null of no cointegration can only be accepted for four cases.

3.4 Results of the cointegration analysis in the presence of structural change

We tested for a bivariate cointegration relationship, using the Gregory and Hansen (1996a, b) test, between each individual stock price and the general MERVAL stock price index in the Argentinean stock market. Results of the residual-based tests for cointegration in models with regime shifts are displayed in Table 7. Estimated break-points from the ADF test are retained. In almost of cases, the t-statistics indicate that the null of no cointegration cannot be rejected at significance levels calculated by Gregory and Hansen (1996a, b), which means that the long-run relationship between prices is not described better by a model with regime shift.

Table 4 ADF Unit root test on individual series

	Series in logarithms		Series in first differences		I(d)
	t-Statistic	p value	t-Statistic	p value	
MERVAL	−1.0582[c]	0.9332	−20.7764***[c]	0.0000	I(1)
ALUA	0.3178[a]	0.777	−12.5946***[c]	0.0000	I(1)
BMA	−1.6013[c]	0.7911	−23.6758***[c]	0.0000	I(1)
FRAN	−1.6869[c]	0.7555	−21.9186***[c]	0.0000	I(1)
EDN	−0.3293[c]	0.9896	−18.6495***[c]	0.0000	I(1)
GGAL	−1.8314[c]	0.6877	−20.1207***[c]	0.0000	I(1)
PAMP	−0.5104[c]	0.9828	−18.9273***[c]	0.0000	I(1)
APBR	−2.3301[b]	0.1630	−19.6149***[a]	0.0000	I(1)
PESA	−2.3597[c]	0.4002	−21.8446***[a]	0.0000	I(1)
COME	−2.0793[c]	0.5552	−20.4647***[a]	0.0000	I(1)
TECO2	−2.0093[c]	0.5940	−21.9459***[a]	0.0000	I(1)
TS	−2.2655[b]	0.1839	−19.7306***[a]	0.0000	I(1)
ERAR	−0.9345[a]	0.3113	−19.5508***[a]	0.0000	I(1)
YPFD	0.8844[c]	0.8991	−17.9609***[a]	0.0000	I(1)

This table reports the results of the Augmented Dickey–Fuller (ADF) test applied to individual series. The tests are based on the null hypothesis of a unit root. For each series, column 2 refers to the variable in logarithms, and column 4 to the first-differenced variable

* (resp. **, ***): rejection of the null hypothesis at the 10 % (resp. 5, 1 %) significance level

[a] Model without constant, nor deterministic trend, [b] model with constant, without deterministic trend, [c] model with constant and deterministic trend

Table 5 The estimated long-run equilibrium relationships

Series	ξ_0		ξ_1	
	Coefficient	p value	Coefficient	p value
ALUA-MERVAL	−0.653**	0.013	0.250***	0.0000
BMA-MERVAL	−6.507***	0.0000	1.130***	0.0000
FRAN-MERVAL	−7.074***	0.0000	1.190***	0.0000
EDN-MERVAL	−5.7434***	0.0000	0.7917***	0.0000
GGAL-MERVAL	−10.833***	0.0000	1.523***	0.0000
PAMP-MERVAL	−3.585***	0.0000	0.527***	0.0000
APBR-MERVAL	3.803***	0.0000	0.068**	0.0330
PESA-MERVAL	6.490***	0.0000	−0.521***	0.0000
COME-MERVAL	−5.959***	0.0000	0.680***	0.0000
TECO2-MERVAL	−5.408***	0.0000	1.040***	0.0000
TS-MERVAL	−1.633***	0.0000	0.783***	0.0000
ERAR-MERVAL	8.669***	0.0000	−0.803***	0.0000
YPFD-MERVAL	0.860***	0.0000	0.528***	0.0000

***, ** and * indicate significance levels at 1, 5 and 10 %, respectively. 2. The long-run equilibrium relationship is $\boldsymbol{Y_{1t}} = \boldsymbol{\xi_0} + \boldsymbol{\xi_1 Y_{2t}} + \boldsymbol{\varepsilon_t}$ where $\boldsymbol{Y_{1t}}$ is the logarithm of the individual stock price, $\boldsymbol{Y_{2t}}$ indicates the logarithm of the MERVAL stock index and $\boldsymbol{\varepsilon_t}$ is the stochastic disturbance term

Table 6 Estimated adjustment equations using the standard Engle–Granger ADF cointegration test

Series	ρ		*AIC*	Lags (p)	$H_0 : \rho = 0$
	Coefficient	t-stat			
ALUA-MERVAL	−0.009	−1.218	−1244.011	1	No cointegration
BMA-MERVAL	−0.048***	−2.745	−1143.562	1	Cointegration
FRAN-MERVAL	−0.054***	−3.691	−1434.450	1	Cointegration
EDN-MERVAL	−0.010	−1.570	−1021.805	1	No cointegration
GGAL-MERVAL	−0.024**	−2.094	−1372.889	1	Cointegration
PAMP-MERVAL	−0.013*	−1.724	−1256.457	1	Cointegration
APBR-MERVAL	−0.029**	−2.356	−914.528	1	Cointegration
PESA-MERVAL	−0.018*	−1.758	−664.683	1	Cointegration
COME-MERVAL	−0.054***	−3.164	−947.568	1	Cointegration
TECO2-MERVAL	−0.056***	−3.202	−1293.942	1	Cointegration
TS-MERVAL	−0.023	−0.692	−142.944	1	No cointegration
ERAR-MERVAL	−0.012	−1.473	−301.548	1	No cointegration
YPFD-MERVAL	−0.024**	−2.106	−1084.702	1	Cointegration

The notation $\boldsymbol{p}$ is the lag periods of the lagged difference terms, which is decided by the minimum AIC. *, ** and *** denote statistical significance at the 10, 5 and 1 % levels, respectively

3.5 Results of the threshold cointegration analysis

From the Engle–Granger ADF cointegration test, the price transmission mechanism within the Argentinean stock market may be asymmetric. To investigate this possibility, it is necessary to go further than the usual concept of cointegration in order to allow for asymmetric cointegration and thus asymmetric price transmission.

We conduct a nonlinear cointegration analysis by using the threshold autoregression models. A total of four models are considered in this study. They are TAR with $\tau = 0$, consistent TAR with τ estimated, M-TAR with $\tau = 0$ and consistent M-TAR with τ estimated. To address possible serial correlation in the residual series, we select an appropriate lag by specifying a maximum lag of 12. We use AIC, BIC and Ljung–Box Q statistics for diagnostic analyses on the residuals. In most cases, the value of the threshold τ is unknown and has to be estimated along the values of ρ_1 and ρ_2. We follow the Chan's (1993) method to estimate the threshold values for consistent TAR and M-TAR models.

Table 8 illustrates the results of the threshold cointegration tests with an unknown threshold value using consistent TAR and M-TAR models. The τ value is the optimal threshold for the indicator function. Under these conditions, we can reject the null hypothesis of threshold cointegration ($\rho_1 = \rho_2 = 0$) for nine cases, except those for PAMP, PESA, TS and ERAR shares. This means that there exists a cointegrating relationship between these individual prices and the MERVAL stock price index.

Since some of the individual prices are cointegrated with the general MERVAL-index using the consistent TAR or M-TAR models, we examine whether their adjustment coefficients are different across positive and negative errors. This procedure

Table 7 Results of Gregory–Hansen cointegration test

	Level shift model C				Level shift model with trend C/T			
	t-stat	t_0	Lag	Date	t-stat	t_0	Lag	Date
ALUA-MERVAL	−2.575	107	5	2009:05:11	−4.511	169	12	2010:07:19
BMA-MERVAL	−3.339	116	1	2009:07:13	−4.561	77	1	2008:10:13
FRAN-MERVAL	−4.328	206	0	2011:04:04	−4.589	153	9	2010:03:29
EDN-MERVAL	−2.783	72	9	2008:09:08	−4.734	332	0	2013:09:02
GGAL-MERVAL	−3.150	167	1	2010:07:05	−4.544	168	1	2010:07:12
PAMP-MERVAL	−3.254	265	0	2012:05:21	−3.918	272	0	2012:07:09
APBR-MERVAL	−4.041	65	0	2008:07:21	−4.053	63	0	2008:07:07
PESA-MERVAL	−5.038	285	1	2012:10:08	−5.968	288	4	2012:10:29
COME-MERVAL	−3.585	60	0	2008:06:16	−4.347	197	0	2011:01:31
TECO2-MERVAL	−2.723	159	4	2010:05:10	−2.780	159	4	2010:05:10
TS-MERVAL	−1.508	265	0	2012:05:21	−2.706	72	0	2008:09:08
ERAR-MERVAL	−9.691***	252	0	2012:02:20	−9.795***	252	0	2012:02:20
YPFD-MERVAL	−2.917	249	0	2012:01:30	−3.371	64	0	2008:07:14

Table 7 continued

	Regime shift model C/S				Regime shift model with trend C/S/T			
	t-stat	t_0	Lag	Date	t-stat	t_0	Lag	Date
ALUA-MERVAL	−2.821	115	5	2009:07:06	−4.490	138	12	2009:12:14
BMA-MERVAL	−3.815	186	1	2010:11:15	−4.969	119	3	2009:08:03
FRAN-MERVAL	−4.395	209	9	2011:04:25	−5.674	103	0	2009:04:13
EDN-MERVAL	−3.027	126	1	2009:09:21	−5.216	220	0	2011:07:11
GGAL-MERVAL	−3.711	168	1	2010:07:12	−4.695	168	1	2010:07:12
PAMP-MERVAL	−3.657	265	0	2012:05:21	−5.296	227	0	2011:08:29
APBR-MERVAL	−4.166	96	0	2009:02:23	−4.554	96	0	2009:02:23
PESA-MERVAL	−6.333***	285	1	2012:10:08	−7.879***	286	2	2012:10:15
COME-MERVAL	−3.703	125	0	2009:09:14	−4.377	197	0	2011:01:31
TECO2-MERVAL	−3.750	112	0	2009:06:15	−5.223	108	0	2009:05:18
TS-MERVAL	−3.908	331	0	2013:08:26	−5.128	223	0	2011:08:01
ERAR-MERVAL	−9.701***	252	0	2012:02:20	−9.549***	252	0	2012:02:20
YPFD-MERVAL	−4.962	258	0	2012:04:02	−5.634	98	0	2009:03:09

t-stat indicate smallest t-statistics using Gregory–Hansen cointegration test among possible break points. Three asterisks *** (resp. **, *) denote rejection of the null hypothesis at the 1 % (resp. 5, 10 %) significance level. $\boldsymbol{t_0}$ denotes the break point corresponding to the smallest t-statistic

Table 8 Estimated adjustment equations using the threshold cointegration test with a consistent estimate of the threshold value

Series	ρ_1	ρ_2	$\Phi(H_0 : \rho_1 = \rho_2 = 0)$	$F(H_0 : \rho_1 = \rho_2)$	AIC	FLAG	τ	Lags (p)
ALUA-MERVAL	0.029* [1.734]	−0.02** [−2.336]	4.231** (0.0152)	6.769** (0.01)	−1250.067	MTAR	0.024	0
BMA-MERVAL	−0.026 [−1.312]	−0.105*** [−3.195]	5.901*** (0.0029)	4.204** (0.041)	−1145.776	TAR	−0.132	1
FRAN-MERVAL	−0.029 [−1.047]	−0.065*** [−3.716]	7.435*** (0.0007)	1.238 (0.267)	−1433.695	MTAR	0.009	1
EDN-MERVAL	−0.003 [−0.358]	−0.026** [−2.259]	2.617* (0.0743)	2.757* (0.098)	−1022.574	MTAR	−0.028	1
GGAL-MERVAL	−0.035** [−2.565]	0.012 [0.54]	3.436** (0.0331)	3.245* (0.072)	−1373.794	MTAR	−0.028	0
PAMP-MERVAL	−0.019* [−1.845]	−0.004 [−0.415]	1.788 (0.1687)	0.967 (0.326)	−1260.108	TAR	−0.349	0
APBR-MERVAL	0.024 [1.39]	−0.076*** [−4.617]	11.836*** (0.0000)	17.948*** (0.000)	−925.3	MTAR	0.015	6
PESA-MERVAL	−0.031** [−2.041]	−0.007 [−0.502]	2.211 (0.111)	1.327 (0.25)	−664.018	MTAR	0.018	1
COME-MERVAL	−0.039* [−1.749]	−0.073*** [−2.908]	5.759*** (0.0034)	1.024 (0.312)	−952.033	TAR	−0.24	0
TECO2-MERVAL	−0.005 [−0.178]	−0.063*** [−2.801]	3.924** (0.0206)	2.577 (0.109)	−1284.435	MTAR	0.012	6
TS-MERVAL	−0.006 [−0.116]	−0.025 [−0.734]	0.276 (0.7588)	0.078 (0.78)	−144.327	TAR	0.245	0
ERAR-MERVAL	−0.032** [−2.076]	−0.005 [−0.527]	2.293 (0.1024)	2.352 (0.126)	−305.662	TAR	0.859	0
YPFD-MERVAL	−0.044** [−2.216]	−0.016 [−1.128]	2.942* (0.0539)	1.464 (0.227)	−1059.349	TAR	0.138	9

The notation $\boldsymbol{p}$ is the lag periods of lagged difference term, which is decided by the minimum AIC. The $\boldsymbol{\Phi}$-statistic for the null hypothesis $\boldsymbol{\rho_1 = \rho_2 = 0}$ is the threshold cointegration test. It follows a nonstandard distribution with the critical values being calculated following Enders and Siklos (2001). The $\boldsymbol{F}$-statistic for the null hypothesis $\boldsymbol{\rho_1 = \rho_2}$ with two variables in symmetry adjustment follows a standard F distribution. The numbers in the brackets are t-statistics. The numbers in parentheses are p values. *, ** and *** indicate significance at the 10, 5 and 1 % levels, respectively is achieved by verifying the existence of an asymmetric cointegration, i.e., testing the null assumption of $\rho_1 = \rho_2$. Notice that the asymmetry test only makes sense when the two previous tests reject the null hypothesis. That is, if the ρ_i coefficients estimated for the threshold are significantly different from zero, then the regression is nontrivial and testing for symmetry makes all the sense. As shown in Table 8, we only found limited evidence of asymmetric price transmission for the “ALUA”, “BMA”, “EDN”, “GGAL” and “APBR” firms, and the results appear to be inconclusive for the remaining stocks. Therefore, these individual stock prices became cointegrated with the MERVAL-index, the adjustment mechanism is asymmetric and the speed of adjustment to the equilibrium is different when the last equilibrium error has different signs. This means that the change in the equilibrium error has a different impact on the adjustment speed to the new equilibrium. According to Anderson (1997), asymmetric cointegration approach better describes the relationships between financial variables.

For instance, focusing on the results from the consistent M-TAR model for the BMA-MERVAL bivariate price series, the Φ-test for the null hypothesis of no cointegration has a statistic of 5.901 and it is highly significant at the 1 % level. Thus, ALUA and MERVAL are cointegrated with threshold adjustment. Furthermore, the F statistic for the null hypothesis of symmetric adjustment has a value of 4.204 and it is also significant at the 5 % level. Therefore, the adjustment process is asymmetric when the BMA and MERVAL stock prices adjust to achieve the long-term equilibrium. The point estimate for the price adjustment is -0.026 for positive shocks and -0.105 for negative shocks. Positive deviations from the long-term equilibrium resulting from increases in BMA stock price or increases in MERVAL stock index ($\Delta\hat{\varepsilon}_{t-1} \geq -0.132$) are eliminated at 2.6 % per week. Negative deviations from the long-term equilibrium resulting from decreases in the BMA stock price or increases in the MERVAL stock index ($\Delta\hat{\varepsilon}_{t-1} < -0.132$) are eliminated at a rate of 10.5 % per week. In other words, positive deviations take about 26 months months ($1/0.026 = 38.46$ weeks) to be fully digested while negative deviations take about 9.52 weeks only ($1/0.105 = 9.52$ weeks). Therefore, there is substantially faster convergence for negative (below threshold) deviations from long-term equilibrium than positive (above threshold) deviations. The same conclusion is made for the EDN and APBR shares. Nevertheless, for the ALUA and GGAL shares, the findings indicate that there is a significantly faster convergence for positive deviations from long-term equilibrium than negative deviations.

3.6 Results of the asymmetric error correction model

In light of the weight of evidence in support of asymmetric adjustments, we could use an asymmetric error correction model to investigate the movement of the stock price series in a long-run equilibrium relationship. The asymmetric error correction model with threshold cointegration is estimated, and the results are reported in Tables 9 and 10. Diagnostic analyses on the residuals with AIC, BIC and Ljung–Box Q statistics select a lag of four for the models.

For the ALUA and MERVAL pair of variables, the consistent M-TAR model is the best from the threshold cointegration analyses and the error correction terms are constructed using Eqs. (13) and (15). Results show that ALUA is cointegrated with

Table 9 Results of the asymmetric error correction models with threshold cointegration

Item	ALUA_MERVAL (C-M-TAR, lag = 4)				BMA_MERVAL (C-TAR, lag = 4)				EDN_MERVAL (C-M-TAR, lag = 4)			
	MERVAL		ALUA		MERVAL		BMA		MERVAL		EDN	
	Estimate	t.statistic	Estimate	t.statistic	Estimate	t.statistic	Estimate	t.statistic	Estimate	t.statistic	Estimate	t.statistic
Estimate												
θ	0.007	1.393	−0.003	−0.49	−0.001	−0.237	−0.008	−0.953	0.005	0.976	−0.012	−1.288
α_1^+	0.292**	2.452	0.341**	2.515	0.357***	2.785	0.483**	2.336	0.172	1.516	0.29	1.524
α_2^+	−0.026	−0.223	0.09	0.674	0.038	0.302	0.28	1.373	−0.024	−0.21	0.097	0.508
α_3^+	−0.139	−1.174	−0.094	−0.696	−0.207*	−1.654	−0.512**	−2.54	−0.077	−0.683	0.158	0.834
α_4^+	−0.014	−0.115	−0.197	−1.471	−0.044	−0.365	0.085	0.439	0.009	0.082	0.206	1.102
α_1^-	−0.458***	−3.853	−0.436***	−3.225	−0.232**	−2.123	0.375**	2.131	−0.282***	−2.609	−0.287.	−1.584
α_2^-	0.032	0.256	0.386***	2.698	0.355***	3.02	0.31	1.636	0.198*	1.786	0.59***	3.187
α_3^-	0.125	0.99	0.223	1.551	−0.069	−0.559	0.318	1.594	−0.077	−0.677	0.044	0.232
α_4^-	−0.031	−0.244	−0.005	−0.036	−0.058	−0.456	−0.241	−1.178	−0.059	−0.514	−0.03	−0.156
β_1^+	−0.161*	−1.657	−0.045	−0.409	−0.131*	−1.704	−0.162	−1.31	0.069	1.094	0.269**	2.568
β_2^+	0.026	0.259	0.084	0.751	0.012	0.161	−0.123	−1.006	0.053	0.834	−0.024	−0.228
β_3^+	0.114	1.201	0.079	0.734	0.166**	2.176	0.27**	2.2	−0.021	−0.333	0.011	0.105
β_4^+	−0.018	−0.183	0.056	0.5	0.033	0.507	−0.026	−0.251	−0.062	−0.995	−0.187*	−1.788
β_1^-	0.3***	2.742	0.064	0.511	−0.007	−0.097	−0.533***	−4.667	−0.02	−0.292	−0.123	−1.069
β_2^-	0.198*	1.759	−0.081	−0.637	−0.147*	−1.789	−0.039	−0.297	−0.005	−0.066	−0.117	−1.006
β_3^-	−0.117	−1.039	−0.091	−0.707	0.052	0.642	−0.057	−0.437	0.14**	2.049	0.015	0.131
β_4^-	0.123	1.092	0.102	0.801	0.146*	1.816	0.088	0.677	0.155**	2.262	0.172.	1.5
δ^+	−0.004	−0.219	0.019	0.93	0.023	1.195	0.007	0.218	−0.008	−1.296	−0.002	−0.229
δ^-	−0.033***	−3.641	−0.024**	−2.356	−0.009	−0.261	−0.117**	−2.172	−0.008	−0.943	−0.032**	−2.219

Table 9 continued

item	ALUA_MERVAL (C-M-TAR, lag = 4)				BMA_MERVAL (C-TAR, lag = 4)				EDN_MERVAL (C-M-TAR, lag = 4)			
s	MERVAL		ALUA		MERVAL		BMA		MERVAL		EDN	
	Estimate	*t*.statistic	Estimate	*t*.statistic	Estimate	*t*.statistic	Estimate	*t*.statistic	Estimate	*t*.statistic	Estimate	*t*.statistic
$H_{01} : \alpha_i^+ = \alpha_i^- = 0$ for all lags	2.397**	[0.02]	3.258***	[0.000]	2.46**	[0.01]	3.126***	[0.000]	1.377	[0.2]	2.067**	[0.04]
$H_{02} : \beta_i^+ = \beta_i^- = 0$ for all lags	1.757*	[0.08]	0.431	[0.9]	1.472	[0.17]	4.597***	[0.000]	1.533	[0.14]	1.497	[0.16]
$H_{03} : \alpha_2^+ = \alpha_2^-$	0.092	[0.76]	1.825	[0.18]	2.831*	[0.09]	0.01	[0.92]	1.567	[0.21]	2.777*	[0.1]
$H_{04} : \beta_4^+ = \beta_4^-$	0.7	[0.4]	0.059	[0.81]	1.123	[0.29]	0.432	[0.51]	4.41**	[0.04]	4.311**	[0.04]
$H_{05} : \sum_{i=1}^4 \alpha_i^+ = \sum_{i=1}^4 \alpha_i^-$	1.409	[0.24]	0.004	[0.95]	0.267	[0.6]	0.844	[0.36]	1.247	[0.26]	0.915	[0.34]
$H_{06} : \sum_{i=1}^4 \beta_i^+ = \sum_{i=1}^4 \beta_i^-$	2.669	[0.1]	0.227	[0.63]	0.051	[0.82]	3.962**	[0.05]	2.097	[0.15]	0.21	[0.65]
$H_{07} : \delta^+ = \delta^-$	2.255	[0.13]	3.802*	[0.05]	0.628	[0.43]	3.685*	[0.06]	0.001	[0.98]	2.824*	[0.09]
Diagnostics												
R^2	0.103	–	0.114	–	0.077	–	0.136		0.078	–	0.099	–
$\bar{R}^2$	0.059	–	0.071	–	0.031	–	0.094		0.033	–	0.055	–
AIC	−1232.549	–	−1133.162	–	−1221.272	–	−853.929	–	−1221.834	–	−825.450	–
BIC	−1153.484	–	–1054.098	–	−1142.207	–	−774.864	–	−1142.769	–	−746.385	–
$Q_{LB}(4)$	0.984	–	0.998	–	0.992	–	0.971	–	0.988	–	0.998	–
$Q_{LB}(8)$	0.853	–	0.969	–	0.826	–	0.960	–	0.950	–	0.956	–
$Q_{LB}(12)$	0.913	–	0.937	–	0.890	–	0.979	–	0.902	–	0.997	–

Numbers in brackets are p values. For the hypotheses, H_{01} and H_{02} are Granger causality tests, H_{03} and H_{04} evaluated distributed lag asymmetric effect, H_{05} and H_{06} assess the cumulative asymmetric effect, and H_{07} is about equilibrium adjustment path asymmetric effect

* Denotes significance at the 10 % level

** Denotes significance at the 5 % level

*** Denotes significance at the 1 % level

Table 10 Results of the asymmetric error correction models with threshold cointegration

Item	GGAL_MERVAL (C-M-TAR, lag = 4)				APBR_MERVAL (C-M-TAR, lag = 4)			
	MERVAL		GGAL		MERVAL		APBR	
	Estimate	*t*.statistic	Estimate	*t*.statistic	Estimate	*t*.statistic	Estimate	*t*.statistic
Estimate								
θ	0.001	0.145	0.002	0.333	0.002	0.37	0.002	0.298
α_1^+	0.375**	2.503	0.183	0.859	0.155	1.329	−0.088	−0.486
α_2^+	−0.077	−0.524	−0.084	−0.4	−0.072	−0.609	−0.103	−0.57
α_3^+	−0.051	−0.349	−0.22	−1.054	0.005	0.039	0.148	0.81
α_4^+	0.1	0.713	0.135	0.677	−0.11	−0.923	−0.252	−1.365
α_1^-	−0.279*	−1.654	−0.083	−0.347	−0.242**	−2.458	−0.069	−0.451
α_2^-	0.361**	2.105	0.791***	3.245	0.218**	2.144	0.218	1.391
α_3^-	0.022	0.125	0.091	0.368	0.099	0.966	0.106	0.665
α_4^-	−0.047	−0.269	−0.135	−0.544	0.15	1.453	0.326**	2.037
β_1^+	−0.12	−1.283	0.027	0.205	0.1	1.222	0.261**	2.067
β_2^+	0.114	1.235	0.119	0.907	0.072	0.891	−0.037	−0.293
β_3^+	−0.002	−0.023	0.089	0.665	−0.127	−1.566	−0.197	−1.569
β_4^+	−0.105	−1.137	−0.05	−0.378	0.129.	1.604	0.072	0.584
β_1^-	0.009	0.067	−0.111	−0.61	0.021	0.378	−0.064	−0.757
β_2^-	−0.146	−1.152	−0.364**	−2.018	0.023	0.424	−0.009	−0.108
β_3^-	0.009	0.07	0.037	0.209	0.011	0.198	−0.066	−0.787
β_4^-	0.153	1.225	0.183	1.027	−0.087.	−1.598	−0.187**	−2.231
δ^+	0.018	1.052	−0.008	−0.337	0.0001	0.033	0.016	0.848
δ^-	−0.047*	−1.694	−0.071*	−1.781	−0.03**	−2.559	−0.081***	−4.398
$H_{01}: \alpha_i^+ = \alpha_i^- = 0$ for all lags	1.577	[0.13]	1.699	[0.1]	1.775*	[0.08]	1.158	[0.32]

Table 10 continued

item	GGAL_MERVAL (C-M-TAR, lag = 4)				APBR_MERVAL (C-M-TAR, lag = 4)			
	MERVAL		GGAL		MERVAL		APBR	
	Estimate	t.statistic	Estimate	t.statistic	Estimate	t.statistic	Estimate	t.statistic
$H_{02} : \beta_i^+ = \beta_i^- = 0$ for all lags	0.88	[0.53]	0.917	[0.5]	1.234	[0.28]	1.571	[0.13]
$H_{03} : \alpha_2^+ = \alpha_2^-$	3.127*	[0.08]	6.164**	[0.01]	2.757*	[0.1]	1.427	[0.23]
$H_{04} : \beta_4^+ = \beta_4^-$	2.302.	[0.13]	0.92	[0.34]	4.246**	[0.04]	2.584	[0.11]
$H_{05} : \sum_{i=1}^4 \alpha_i^+ = \sum_{i=1}^4 \alpha_i^-$	0.386	[0.54]	0.958	[0.33]	0.603	[0.44]	3.177*	[0.08]
$H_{06} : \sum_{i=1}^4 \beta_i^+ = \sum_{i=1}^4 \beta_i^-$	0.151	[0.7]	0.772	[0.38]	1.271	[0.26]	2.279	[0.13]
$H_{07} : \delta^+ = \delta^-$	3.993**	[0.05]	1.813	[0.18]	3.551*	[0.06]	14.788***	[0.000]
Diagnostics								
R^2	0.073	–	0.068	–	0.082	–	0.105	–
$\bar{R}^2$	0.027	–	0.022	–	0.037	–	0.060	–
AIC	−1219.784	–	−948.073	–	−1223.736	–	−888.610	–
BIC	−1140.719	–	−869.008	–	−1144.671	–	−809.545	–
$Q_{LB}(4)$	0.987	–	1.000	–	0.953	–	0.965	–
$Q_{LB}(8)$	0.339	–	0.831	–	0.258	–	0.239	–
$Q_{LB}(12)$	0.411	–	0.923	–	0.472	–	0.366	–

Numbers in brackets are p values. For the hypotheses, H_{01} and H_{02} are Granger causality tests, H_{03} and H_{04} evaluated distributed lag asymmetric effect, H_{05} and H_{06} assess the cumulative asymmetric effect, and H_{07} is about equilibrium adjustment path asymmetric effect

* Denotes significance at the 10 % level

** Denotes significance at the 5 % level

*** Denotes significance at the 1 % level

MERVAL and it also exhibits asymmetric adjustments. In the equation for MERVAL, there are six coefficients statistically significant at the 1, 5 and 10 % levels, respectively, (i.e., α_1^-, β_1^-, δ^-, α_1^+, β_1^+ and β_2^-). In equation for ALUA, there are four significant coefficients (i.e., α_1^+, α_1^-, α_2^- and δ^-). Besides, the short-term equilibrium adjustment process mainly occurs with MERVAL-index since $\delta^+ = \delta^-$. Moreover, according to Chen et al. (2013), there are three situations to reduce the price deviations between the two stocks if they are cointegrated. Given the case MERVAL-index price is larger than ALUA-share price, there are three situations to reduce the price deviations: (i) MERVAL-index price goes down and ALUA-share price goes up; (ii) MERVAL-index price goes down and ALUA-share price goes down as well, but MERVAL-index price drops more; (iii) MERVAL-index price goes up and ALUA-share price goes up, but MERVAL-index price increases less.

In our results, for regimes with positive shocks (MERVAL-index price is higher than ALUA-share price), the adjustment coefficient for MERVAL-index is −0.004 and 0.019 for ALUA-share, which means that, in the next period, ALUA-share price will go up and MERVAL-index price will go down, and thus, the price deviation will decrease. For regimes with negative shocks (MERVAL-index price is lower than ALUA-share price), the adjustment coefficient for MERVAL-index is −0.033 and −0.024 for ALUA-share, which means that, in the next period, ALUA-share price will go down and MERVAL-index price will go down as well, but ALUA-share drops more and thus the price deviation will decrease. Diagnostic analyses on the residuals with Ljung–Box Q statistics select a lag of four for the model. The $\bar{R}^2$ value is 0.059 for the MERVAL-index and 0.071 for the ALUA-share. Moreover, the AIC and BIC statistics for the ALUA-share are both larger than those for the MERVAL-index. This means that the model specification is better fitted on the ALUA-share.

Using the estimation results of the asymmetric ECM with threshold cointegration, we also conduct the hypothesis testing described in Sect. 2 (paragraph 2.3). The hypotheses of Granger causality between the series are assessed with F-tests. The F-statistic of 3.258 reveals that MERVAL does Granger cause ALUA. Besides, the F-statistic of 1.757 indicates that ALUA does Granger cause MERVAL. This indicates that, in the short-term, both stocks affect each other. Similarly, the F-statistic of 2.397 for MERVAL discloses that the lagged price series have significant impacts on its own price. Furthermore, the F-statistic of 0.431 for ALUA reveals that the lagged price series have no significant impacts on its own price. Thus, in the short term, MERVAL and ALUA have been evolving more dependently.

Several kinds of hypotheses are examined for asymmetric price transmission. The first one is the *distributed lag asymmetric effect*. In each price equation, the equality of the corresponding positive and negative coefficients for each of the four lags is tested; in total, there are eight F tests for this hypothesis. It turns out that none of them is statistically significant and distributed lag asymmetric effect does not exist.

Furthermore, the *cumulative asymmetric effects* are also examined. The largest F-statistic is 2.669 but none of the four statistics are significant at the conventional level. Thus, cumulative effects are symmetric. The final type of asymmetry examined is the *momentum equilibrium adjustment path asymmetries*. For MERVAL, the F-statistic is 2.255 with a t value of 0.13. The point estimates of the coefficients for the error correction terms are −0.004 for positive error correction term and −0.033

for the negative one. In contrast, for ALUA-share, the F-statistic is 3.802 with a p value of 0.05. Thus, there is momentum equilibrium adjustment asymmetry. The point estimates are 0.019 with a t value of 0.93 for positive deviations and -0.024 with a t value of -2.356 for negative deviations. The magnitude suggests that in the short-term the ALUA responds to the positive deviations by 1.9 % in a week but by 2.4 % to negative deviations. Measured in response time, positive and negative deviations take, respectively, 52.63 and 41.67 weeks to be fully digested. Therefore, in the short-term, ALUA has a much faster reaction to negative deviations from long-term equilibrium than positive deviations.

Results from the consistent TAR model for the BMA-MERVAL pair of stock prices (see Table 8) show that BMA is cointegrated with MERVAL and also show signs of asymmetric adjustment. In addition, we find that the short-term equilibrium adjustment process mainly occurs with the MERVAL-index since $\delta^{+} = \delta^{-}$. Moreover, there exist three situations to reduce the price deviations between the two stocks: (i) MERVAL-index price goes down and BMA-share price goes up; (ii) MERVAL-index price goes down and BMA-share price goes down as well, but MERVAL-index price drops more; (iii) MERVAL-index price goes up and BMA-share price goes up, but MERVAL-index price increases less.

In our results, for regimes with positive shocks (MERVAL-index price is higher than BMA-share price), the adjustment coefficient for MERVAL-index is 0.023 and 0.007 for BMA-share, which means that, in the next period, MERVAL-index price will go up and BMA-share price will go down, thus, the price deviation will decrease. For regimes with negative shocks (MERVAL-index price is lower than BMA-share price), the adjustment coefficient for MERVAL-index is -0.009 and -0.117 for BMA-share, which means that, in the next period, MERVAL-index price will go down and BMA-share price will go down as well, but MERVAL-index drops more and thus the price deviation will decrease. Diagnostic analyses on the residuals with Ljung–Box Q statistics select a lag of four for the model. The $\bar{R}^2$ value is 0.031 for the MERVAL-index and 0.094 for the BMA-share. Moreover, the AIC and BIC statistics for the BMA-share are both larger than those for the MERVAL-index. This indicates that the model specification is better fitted on the BMA-share.

The assumptions of Granger causality between these series are evaluated with F tests. The F-statistic of 3.126 and the p value of 0.000 reveal that MERVAL does Granger cause the BMA price series. However, the F-statistic of 1.472 indicates that the BMA stock price does not Granger cause the MERVAL stock index. Similarly, the F-statistic of 2.46 for MERVAL discloses that the lagged price series have significant impacts on its own price. Thus, in the short term, the MERVAL price series has been evolving more independently while the BMA price series has been dependent on the MERVAL stock index in the previous periods. The first assumption for asymmetric price transmission states that the distributed lag asymmetric effect is statistically significant for both series. For the cumulative asymmetric effects, the largest F-statistic is 3.962 but only one of the four statistics is statistically significant at the 5 % significance level. Thus, there have been some asymmetric cumulative effects. Concerning the momentum equilibrium adjustment path asymmetries, the F-statistic is 0.628 for MERVAL with a p value of 0.43. The point estimates of the coefficients for the error correction terms are 0.023 for positive error correction term and -0.009 for the negative one. In contrast, for the BMA price series, the F-statistic is 3.685 with a p value of 0.06, indicating the existence of a momentum equilibrium adjustment asymmetry. The point estimates are 0.007 with a t value of 0.218 for positive deviations and -0.117 with a t value of -2.172 for negative deviations. The magnitude suggests that, in the short term, the BMA price series responds to the positive deviations by 0.7 % in a week but by 11.7 % to negative deviations. Measured in response time, positive deviations take 142.86 weeks to be fully digested while negative deviations take 8.55 weeks only. Therefore, in the short-term, the BMA price series has a much slower reaction to positive deviations from long-term equilibrium than negative deviations.

Results from the consistent M-TAR model for the EDN-MERVAL pair of stock prices (see Table 8) show that EDN is cointegrated with MERVAL and also show signs of asymmetric adjustment. Besides, the short-term equilibrium adjustment process mainly occurs with the MERVAL-index since $\delta^+ = \delta^-$. Likewise, there exist three situations to reduce the price deviations between the two stocks: (i) MERVAL-index price goes down and EDN-share price goes up; (ii) MERVAL-index price goes down and EDN-share price goes down as well, but MERVAL-index price drops more; (iii) MERVAL-index price goes up and EDN-share price goes up, but MERVAL-index price increases less.

In our findings, for regimes with positive shocks (MERVAL-index price is higher than EDN-share price), the adjustment coefficient for MERVAL-index is -0.008 and -0.002 for EDN-share, which means that, in the next period, EDN-share price will go up and MERVAL-index price will go down, thus, the price deviation will decrease. For regimes with negative shocks (MERVAL-index price is lower than EDN-share price), the adjustment coefficient for MERVAL-index is -0.008 and -0.032 for EDN-share, which means that, in the next period, MERVAL-index price will go down and EDN-share price will go down as well, but MERVAL-index drops more and thus the price deviation will decrease. Diagnostic analyses on the residuals with Ljung–Box Q statistics select a lag of four for the model. The $\bar{R}^2$ value is 0.033 for the MERVAL-index and 0.055 for the EDN-share. Moreover, the AIC and BIC statistics for the EDN-share are both larger than those for the MERVAL-index. This indicates that the model specification is better fitted on the EDN-share.

The assumptions of Granger causality between these series are assessed with F tests. The F-statistic of 2.067 and the p value of 0.04 reveal that MERVAL does Granger cause the EDN price series. Nevertheless, the F-statistic of 1.533 shows that the EDN stock price does not Granger cause the MERVAL stock index. Likewise, the F-statistics of 1.377 for MERVAL discloses that the lagged price series have not significant impacts on its own price. Thus, in the short term, the MERVAL price series has not been evolving more independently while the EDN price series has been dependent on the MERVAL stock index in the previous periods. The first assumption for asymmetric price transmission states that the distributed lag asymmetric effect is statistically significant for both series. For the cumulative asymmetric effects, the largest F-statistic is 2.097 but none of the four statistics is statistically significant at the conventional significance level. Thus, there have not been asymmetric cumulative effects. Concerning the momentum equilibrium adjustment path asymmetries, the F-statistic is 0.001 for MERVAL with a p value of 0.98. The point estimates of the coefficients for the error correction terms are -0.008 for positive error correction term, with a t value of -1.296, and -0.008 for the negative one with a t value of -0.943. In contrast, for the EDN price series, the F-statistic is 2.824 with a p value of 0.09, indicating the existence of a momentum equilibrium adjustment asymmetry. The point estimates are -0.002 with a t value of -0.229 for positive deviations and -0.032 with a t value of -2.219 for negative deviations. The magnitude suggests that, in the short-term, the EDN price series responds to the positive deviations by 0.2 % in a week but by 3.2 % to negative deviations. Measured in response time, positive deviations take 500 weeks to be fully digested while negative deviations take 31.25 weeks only. Therefore, in the short-term, the BMA price series has a much slower reaction to negative deviations from long-term equilibrium than positive deviations.

The empirical results from the consistent M-TAR model for the GGAL-MERVAL pair of stock prices (see Table 8) show that GGAL is cointegrated with MERVAL and also show signs of asymmetric adjustment. Besides, the short-term equilibrium adjustment process mainly occurs with GGAL index since $\delta^{+} = \delta^{-}$. Likewise, there exist three situations to reduce the price deviations between the two stocks: (i) MERVAL-index price goes down and GGAL-share price goes up; (ii) MERVAL-index price goes down and EDN-share price goes down as well, but MERVAL-index price drops more; (iii) MERVAL-index price goes up and GGAL-share price goes up, but MERVAL-index price increases less.

In our findings, for regimes with positive shocks (MERVAL-index price is higher than GGAL-share price), the adjustment coefficient for MERVAL-index is 0.018 and -0.008 for GGAL-share, which means that, in the next period, MERVAL-index price will go up and GGAL-share price will go down, thus, the price deviation will decrease. For regimes with negative shocks (MERVAL-index price is lower than GGAL-share price), the adjustment coefficient for MERVAL-index is -0.047 and -0.071 for GGAL-share, which means that, in the next period, MERVAL-index price will go down and GGAL-share price will go down as well, but MERVAL-index drops more and thus the price deviation will decrease. Diagnostic analyses on the residuals with Ljung–Box Q statistics select a lag of four for the model. The $\bar{R}^2$ value is 0.027 for the MERVAL-index and 0.022 for the GGAL-share. Moreover, the AIC and BIC statistics for the GGAL-share are both larger than those for the MERVAL-index. This shows that the model specification is better fitted on the GGAL-share.

The F-statistic of 1.699 and the p value of 0.1 reveal that MERVAL does not Granger cause the GGAL price series. Moreover, the F-statistic of 0.88 indicates that the GGAL stock price does not Granger cause the MERVAL stock index. Similarly, the F-statistics of 1.577 for MERVAL discloses that the lagged price series have not significant impacts on its own price. Thus, in the short-term, the GGAL price series has been independent on the MERVAL stock index in the previous periods. Besides, the distributed lag asymmetric effect is statistically significant for both stock price series. For the cumulative asymmetric effects, the largest F-statistic is 0.958 but none of the four statistics is statistically significant at the corresponding significance level. Regarding the momentum equilibrium adjustment path asymmetries, the F-statistic is 3.993 for MERVAL with a p value of 0.05. The point estimates of the coefficients for the error correction terms are 0.018 for positive error correction term with a t value of 1.052, and -0.047 for the negative one with a t value of -1.694. On the contrary, for the GGAL price series, the F statistic is 1.813 with a p value of 0.18, indicating the absence of a momentum equilibrium adjustment asymmetry. The point estimates are -0.008 with a t value of -0.337 for positive deviations and -0.071 with a t value of -1.781 for negative deviations. The magnitude suggests that in the short-term the GGAL price series responds to the positive deviations by 0.8 % in a week but by 7.1 % to negative deviations. Measured in response time, positive deviations take 125 weeks to be fully digested while negative deviations take 14.08 weeks only. Therefore, in the short-term, the GGAL price series has a much faster reaction to negative deviations from long-term equilibrium than positive deviations.

The empirical findings from the consistent M-TAR model for the APBR-MERVAL pair of stock prices (see Table 8) show that APBR is cointegrated with MERVAL and also show signs of asymmetric adjustment. In addition, we find that the short-term equilibrium adjustment process mainly occurs with MERVAL-index since $\delta^{+} = \delta^{-}$. Furthermore, there exist three situations to reduce the price deviations between the two stocks: (i) MERVAL-index price goes down and APBR-share price goes up; (ii) MERVAL-index price goes down and APBR-share price goes down as well, but MERVAL-index price drops more; (iii) MERVAL-index price goes up and APBR-share price goes up, but MERVAL-index price increases less.

In our findings, for regimes with positive shocks (MERVAL-index price is higher than APBR-share price), the adjustment coefficient for MERVAL-index is 0.0001 and 0.016 for APBR-share, which means that, in the next period, APBR-share price will go up and MERVAL-index price will go down, thus, the price deviation will decrease. For regimes with negative shocks (MERVAL-index price is lower than APBR-share price), the adjustment coefficient for MERVAL-index is -0.03 and -0.081 for APBR-share, which means that, in the next period, MERVAL-index price will go down and APBR-share price will go down as well, but MERVAL-index drops more and thus the price deviation will decrease. Diagnostic analyses on the residuals with Ljung–Box Q statistics select a lag of four for the model. The $\bar{R}^2$ value is 0.037 for the MERVAL-index and 0.060 for the APBR-share. Moreover, the AIC and BIC statistics for the APBR-share are both larger than those for the MERVAL-index. This shows that the model specification is better fitted on the APBR-share.

The F-statistic of 1.158 and the p value of 0.32 reveal that MERVAL does Granger cause the APBR price series. Besides, the F-statistic of 1.234 with a p value of 0.28 indicates that the APBR stock price does not Granger cause the MERVAL stock index. In the same way, the F-statistic of 1.775 with a p value of 0.08, for MERVAL, discloses that the lagged price series have significant impacts on its own price. Thus, in the short-term, the MERVAL price series has been evolving more independently while the APBR price series has been dependent on the MERVAL stock index in the previous periods. In addition, the distributed lag asymmetric effect is only statistically significant for MERVAL price series. For the cumulative asymmetric effects, the largest F-statistic is 3.177, with a p value of 0.08, but only one of the four statistics is statistically significant at the 10 % significance level. Thus, there exist some asymmetric cumulative effects. Concerning the momentum equilibrium adjustment path asymmetries, the F-statistic is 3.551 for MERVAL with a p value of 0.06. The point estimates of the coefficients for the error correction terms are 0.0001 for positive error correction term and -0.03 for the negative one. In contrast, for the APBR price series, the F-statistic is 14.788 with a p value of 0.000, indicating the existence of a momentum equilibrium adjustment asymmetry. The point estimates are 0.016 with a t value of 0.848 for positive deviations and −0.081 with a t value of −4.398 for negative deviations. The magnitude suggests that in the short term the APBR price series responds to the positive deviations by 1.6 % in a week but by 8.1 % to negative deviations. Measured in response time, positive deviations take 62.5 weeks to be fully eliminated, while negative deviations take 12.35 weeks only. Therefore, in the short term, the APBR price series has a much faster reaction to negative deviations from long-term equilibrium than positive deviations.

4 Pairs trading rules

Pairs Trading is a trading or investment strategy used to exploit financial markets that are out of equilibrium (see Elliott et al. 2005). It is a trading strategy consisting of a long position in one security and a short position in another security in a predetermined ratio. Pairs Trading is also regarded as a special form of Statistical Arbitrage and its idea can be applied to any equilibrium relationship in financial markets.

According to Lin et al. (2006), "Pairs trading" is defined as "a comparative-value form of statistical arbitrage designed to exploit temporary random departures from equilibrium pricing between two shares". As arguing by these authors, the strategy identifies pairs of shares whose prices are driven by the same economic forces, and then trades on any temporary deviations of those two-share prices from their long-run average relationship. In addition, Lin et al. (2006) argue that the arbitrage or risk-free nature of the strategy arises from the opening of opposing positions for each trade-shorting the overvalued share and buying the under-valued share. Furthermore, Lin et al. (2006) argue that the simple statistical techniques (i.e., correlation, covariance, and regression analysis) used for share pairs selection and trading decisions provide an imprecise, simplistic statistical definition of a long-run equilibrium relationship between share prices. Besides, Lin et al. (2006) suggest that these statistics do not necessarily imply mean reversion to a long-run equilibrium price spread.

Due to the deficiencies of the classical statistical techniques, Lin et al. (2006) use cointegration theory to provide a statistically precise foundation for the decisions involved in pairs trading rules. Particularly, they use the linear cointegrating relationship between markets or among individual stocks to design pairs trading rules. They employ cointegration principles to embed a minimum profit condition within a pairs trading strategy. Furthermore, Tourin and Yan (2013) propose a model for analyzing dynamic pairs trading strategies. Their model is explored in an optimal portfolio setting where the portfolio consists of a cash account and two cointegrated stocks. Nevertheless, Chen and Zhu (2015) argue that trading rules based on linear cointegrating relationships cannot provide any information for buy and sell timing. These authors suggest that threshold cointegration models separate all sample periods into different regimes according to the relative value of the threshold variable to the threshold value. They argue that such regime switching is observable and consequently offers buy and sell timing when designing trading rules.

In the previous analysis, we found evidence of asymmetric adjustment mechanism for the "ALUA", "BMA", "EDN", "GGAL" and "APBR" firms. For the "ALUA-MERVAL" pair of stocks, the short-term equilibrium adjustment process mainly occurs with the MERVAL-index, with the adjustment speed faster for a regime with negative deviation than for one with positive deviation. Based on this finding, our trading rule is a pairs trading rule, that is, buy an ALUA-share and sell an MERVAL-index when $\Delta\hat{\varepsilon}_{t-1} \geq 0.024$, and sell an ALUA-share and buy a MERVAL-index when $\Delta\hat{\varepsilon}_{t-1} \leq 0.024$. We evaluate these two trading strategies by calculating the mean forecast trading return (MFTR), defined as follows:

$$\begin{aligned}\text{MFTR}_{\text{MERVAL-ALUA}} = &\frac{1}{n}\sum_{t=m+1}^{T} sign\left(\Delta\hat{\varepsilon}_{t-1} - 0.024\right) y_{\text{ALUA},t}\\ &+\frac{1}{n}\sum_{t=m+1}^{T} sign\left(0.024 - \Delta\hat{\varepsilon}_{t-1}\right) y_{\text{MERVAL},t}\end{aligned}$$

where $T(T = m + n)$ is the total sample size; $y_{\text{MERVAL},t}$ and $y_{\text{ALUA},t}$ are the weekly return of the MERVAL-index and ALUA share; and $\Delta\hat{\varepsilon}_{t-1}$ is the difference of the estimated residual obtained from Eq. (1). The function $sign(x) = \mathbf{1}(x > 0) - \mathbf{1}(x < 0)$ and $\mathbf{1}(\cdot)$ takes the value of 1 if the statement in the parenthesis is true and 0 otherwise.

For the "BMA-MERVAL" pair of stocks, the short-term equilibrium adjustment process mainly occurs with the MERVAL-index, with the adjustment speed faster for negative deviation regimes. Based on this finding, our trading rule is a pairs trading rule, that is, buy a BMA-share and sell a MERVAL-index when $\hat{\varepsilon}_{t-1} \geq -0.132$, and sell a BMA-share and buy a MERVAL-index when $\hat{\varepsilon}_{t-1} \leq -0.132$. We evaluate these two trading strategies by calculating the mean forecast trading return (MFTR), defined as follows:

$$\begin{aligned}\text{MFTR}_{\text{MERVAL-BMA}} = &\frac{1}{n}\sum_{t=m+1}^{T} sign\left(\hat{\varepsilon}_{t-1} - (-0.132)\right) y_{\text{BMA},t}\\ &+\frac{1}{n}\sum_{t=m+1}^{T} sign\left(-0.132 - \hat{\varepsilon}_{t-1}\right) y_{\text{MERVAL},t}\end{aligned}$$

For the "EDN-MERVAL" pair of stocks, the short-term equilibrium adjustment process mainly occurs with the MERVAL-index, with the adjustment speed slower for a regime with negative deviation than for one with positive deviation. Based on this result, our trading rule is a pairs trading rule, that is, buy an EDN-share and sell a MERVAL-index when $\Delta\hat{\varepsilon}_{t-1} \geq -0.028$, and sell an EDN-share and buy a MERVAL-index when $\Delta\hat{\varepsilon}_{t-1} \leq -0.028$. We evaluate these two trading strategies by calculating the mean forecast trading return (MFTR), defined as follows:

$$\begin{aligned}\text{MFTR}_{\text{MERVAL-EDN}} = &\frac{1}{n}\sum_{t=m+1}^{T} sign\left(\Delta\hat{\varepsilon}_{t-1} - (-0.028)\right) y_{\text{EDN},t}\\ &+\frac{1}{n}\sum_{t=m+1}^{T} sign\left(-0.028 - \Delta\hat{\varepsilon}_{t-1}\right) y_{\text{MERVAL},t}\end{aligned}$$

For the "GGAL-MERVAL" pair of stocks, the short-term equilibrium adjustment process mainly occurs with the GGAL-share, with the adjustment speed faster for negative deviation regimes. Based on this finding, our trading rule is a pairs trading rule, that is, buy a MERVAL-index and sell a GGAL-share when $\Delta\hat{\varepsilon}_{t-1} \geq -0.028$, and sell a MERVAL-index and buy a GGAL-share when $\Delta\hat{\varepsilon}_{t-1} \leq -0.028$. We evaluate these two trading strategies by calculating the mean forecast trading return (MFTR), defined as follows:

$$\begin{aligned}\text{MFTR}_{\text{MERVAL-GGAL}} &= \frac{1}{n}\sum_{t=m+1}^{T} sign\left(\Delta\hat{\varepsilon}_{t-1} - (-0.028)\right) y_{\text{MERVAL},t} \\ &\quad + \frac{1}{n}\sum_{t=m+1}^{T} sign\left(-0.028 - \Delta\hat{\varepsilon}_{t-1}\right) y_{\text{GGAL},t}\end{aligned}$$

For the "APBR-MERVAL" pair of stocks, the short-term equilibrium adjustment process mainly occurs with the MERVAL-index, with the adjustment speed faster for a regime with negative deviation than for one with positive deviation. Based on this finding, our trading rule is a pairs trading rule, that is, buy an APBR-share and sell a MERVAL-index when $\Delta\hat{\varepsilon}_{t-1} \geq 0.015$, and sell an APBR-share and buy a MERVAL-index when $\Delta\hat{\varepsilon}_{t-1} \leq 0.015$. We evaluate these two trading strategies by calculating the mean forecast trading return (MFTR), defined as:

$$\begin{aligned}\text{MFTR}_{\text{MERVAL-APBR}} &= \frac{1}{n}\sum_{t=m+1}^{T} sign\left(\Delta\hat{\varepsilon}_{t-1} - 0.015\right) y_{\text{APBR},t} \\ &\quad + \frac{1}{n}\sum_{t=m+1}^{T} sign\left(0.015 - \Delta\hat{\varepsilon}_{t-1}\right) y_{\text{MERVAL},t}\end{aligned}$$

For comparison, we also define the MFTR for a buy-and-hold strategy on MERVAL-index, ALUA, BMA, EDN, GGAL and APBR shares, respectively, as

$$\text{MFTR}_i = \frac{1}{n}\sum_{t=m+1}^{T} y_{i,t}$$

where $i =$ALUA, BMA, EDN, GGAL, APBR, MERVAL.

We let $m = 338$ and $n = 52$. Table 11 reports the MFTRs of the threshold trading rule and the naive buy-and-hold rules. Note that, except the cases of BMA-MERVAL and GGAL-MERVAL pairs of stocks, the threshold trading rule achieves a higher profit than the naive buy-and-hold rule. In this case, threshold trading strategies which consider the asymmetric properties of deviations from the long-run equilibrium are more profitable. This finding illustrates a significant benefit of using threshold cointegration models.

Table 11 Trading-rule profits

Trading strategy	MFTR
Threshold trading (ALUA-MERVAL)	2.470261882
Threshold trading (BMA-MERVAL)	−0.591793906
Threshold trading (EDN-MERVAL)	5.857326789
Threshold trading (GGAL-MERVAL)	−1.658215257
Threshold trading (APBR-MERVAL)	4.2151357
Buy-and-hold on MERVAL-index	1.263277975
Buy-and-hold on ALUA-share	1.675279124
Buy-and-hold on BMA-share	1.042110553
Buy-and-hold on EDN-share	1.736625971
Buy-and-hold on GGAL-share	1.067588507
Buy-and-hold on APBR-share	0.688582441

MFTR denotes the mean forecast trading return. Threshold trading is to buy an x-share and sell an y-share when $\Delta\hat{\boldsymbol{\varepsilon}}_{\boldsymbol{t-1}} \geq \boldsymbol{\tau}$ (or $\hat{\boldsymbol{\varepsilon}}_{\boldsymbol{t-1}} \geq \boldsymbol{\tau}$), and sell an x-share index and buy an y-share index when $\Delta\hat{\boldsymbol{\varepsilon}}_{\boldsymbol{t-1}} < \boldsymbol{\tau}$ (or $\hat{\boldsymbol{\varepsilon}}_{\boldsymbol{t-1}} < \tau$)

5 Conclusions

This article uses the Enders-Siklos asymmetric cointegration test to examine the long-run asymmetric equilibrium relationships between the general national stock index and individual stock market prices within the Argentinean stock market. The asymmetric error correction models extend the standard cointegration models to deal with the problem of low power of unit roots and cointegration tests in the presence of asymmetric adjustment.

The estimated results are presented in the following. First, when the conventional Engle–Granger symmetric cointegration test is used, only the ALUA, EDN, TS and ERAR shares, on the Argentinean stock market, are not cointegrated with the general stock index. Second, we allow for exhibit a statistical structural break in the long-term relationship between prices. Results show that the null of no cointegration cannot be rejected, which means that the long-run relationship between stock prices is not better described by a model with regime shift. Third, the same issue is reexamined by using asymmetric cointegration techniques. The first finding in this study is that the ALUA, BMA, FRAN, EDN, GGAL, APBR, COME, TECO2 and YPFD shares are in fact cointegrated with the general MERVAL-index. The second finding is that only the ALUA, BMA, EDN, GGAL and APBR shares, on the Argentinean stock market, become cointegrated with MERVAL and are in an asymmetric form. Fourth, the transmission between the stock prices, on the Argentinean stock market, has been asymmetric in both the long-term and short-term. The threshold cointegration analysis reveals that in the long-term, the adjustment speed of ALUA and GGAL shares is faster when the deviation from the long-run equilibrium is positive than when it is negative. The opposite result is obtained for BMA, EDN and APBR shares. Similarly, in the short term, the error correction model reveals that the adjustment speed of EDN-share is faster when the deviation from the long-run equilibrium is positive than when it is negative. This implies that EDN-share investors are more likely to overreact to falling stock prices. The results for ALUA, BMA, GGAL and APBR shares show that these price series have a much faster reaction to negative deviations from long-term equilibrium than positive deviations. Additionally, the Granger causality tests are conducted to examine the lead–lag relationship between the stock prices and the general MERVAL stock index on the Argentinean stock market. The test shows that the MERVAL and ALUA have bidirectional causality. Nevertheless, a unidirectional causality is observed between MERVAL and each of the following shares: BMA, EDN and APBR. Finally, we consider a pairs trading rule based on the estimated threshold ECM, which generates a significantly higher profit than a buy-and-hold strategy.

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