Arbitrage and Convergence: Evidence from Mexican ADRs

by

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ABSTRACT

This paper investigates the convergence between the prices of ADRs and the prices of the Mexican traded shares using a sample of 21 dually listed shares. Since both markets have similar trading hours, standard arbitrage considerations should make persistent deviation from price parity rare. We use a STAR model, where the dynamics of convergence to price parity are influenced by the size of the deviation from price parity. Based on different tests, we select the ESTAR model. Deviations from price parity tend to die out quickly; for 14 out of 21 pairs it takes less than two days for the deviations from price parity to be reduced by half. The average half-life of a shock to price parity is 3.1 business days, while the median half-life is 1.1 business days. By allowing a non-linear adjustment process, the average half-life is reduced by more than 50% when compared to the standard linear arbitrage model. We find that several liquidity indicators are positively correlated to the speed of convergence to price parity.

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I. Introduction

In this paper, we study the possible arbitrage opportunities that the American Depository Receipts (ADRs) market provides. Although trading ADRs in the U.S. is U.S. dollar denominated, it should be equivalent to trading the foreign firms' shares without actually trading them in their respective local markets. In the absence of direct or indirect trading barriers, there should not be significant differences between the return distribution of locally traded shares and that of the U.S. traded ADRs.[1] That is, ADRs and their underlying shares are expected to be perfect substitutes and no arbitrage opportunities should prevail. If prices between the ADRs and their underlying shares differ substantially, arbitrage opportunities will arise.

There is a substantial body of literature that studies the potential arbitrage opportunities that the ADRs create. The early studies by Maldonado and Saunders (1983), Kato, Linn and Schallheim (1991), Park and Tavakkol (1994), Miller and Morey (1996) and Karolyi and Stulz (1996) concluded that ADRs do not present any arbitrage opportunities. The only early study that did find some arbitrage opportunities is by Wahab, Lashgari and Cohn (1992). Substantial deviations from arbitrage pricing are consistent with other studies in the literature of dually-listed shares, such as Rosenthal and Young (1990), and Froot and Dabora (2003). As discussed by Gagnon and Karolyi (2003), there are impediments due to market frictions and imperfect information that can seriously limit arbitrage. Gagnon and Karolyi (2003), however, quantify sizable price deviations from price parity and find these deviations to exceed reasonable measures of

[1] Many papers deal with the issue of international barriers to trading, investments, and cash flows movements. See Stulz (1981), Eun and Janakiramanan (1986), Stulz and Wasserfallen (1995) and Domowitz, Glen and Madhavan (1997).

the costs of exploiting them. De Jong, Rosenthal and van Dijk (2004) and Hong and Susmel (2003) show that simple arbitrage strategies based on the deviation from theoretical prices parity can deliver significant profits. These significant deviations from arbitrage pricing have been attributed to market inefficiencies, see Mullainathan and Thaler (2000) and Barberis and Thaler (2003).

The convergence to price parity has also been recently studied. Gagnon and Karolyi (2003) discuss the mechanics of arbitrage in the ADR market. Arbitrage, which involves the issuance and cancellation of ADRs, can take place on the same day, but it usually occurs on an overnight basis. Gagnon and Karolyi (2003) report the average deviation from price parity can persist for up to five days. Some studies, however, find convergence to price parity to be surprisingly slow. For example, De Jong, Rosenthal and van Dijk (2004) find substantial variation in the number of days for which an arbitrageur has to maintain a position before convergence. In some cases, arbitrageurs have to wait for almost 9 years.

In this paper, we focus on the price convergence between the ADRs and their underlying shares. We study Mexican ADRs because the trading hours in Mexico and New York are almost identical, thus, convergence to price parity should not be affected by possible lead-lag informational impact, as analyzed by Kim, Szakmary and Mathur (2000). The majority of the studies in this area have, implicitly, focused on linear convergence to arbitrage parity.[2] Given the complexity of rules, direct and indirect transaction costs, however, non-linear adjustments to price parity deviation are more likely to occur. We use two popular non-linear models for our adjustment specification:

[2] See for instance Kim et al. (2000) for VAR and SUR approaches to analyze the speed of adjustment of ADR prices; and Gagnon and Karolyi (2003) for a standard AR model.

the exponential smooth transition autoregressive (ESTAR) and the logarithmic smooth transition autoregressive (LSTAR). From our estimation results, first, we reject the linear adjustment model; and, second, based on different tests, we select the ESTAR model. Using the ESTAR model, we are able to estimate the half-life of different shocks. We find that price spreads tend to die out quickly, for 14 out of 21 firms it takes less than 2 day for the ADR-underlying price spread to be reduced by half. These results are consistent with the dynamics of arbitrage in the ADR market. Gagnon and Karolyi (2003) mention that although the process of issuance and cancellation of ADRs can take place on the same day; the process usually occurs on an overnight basis. We find that for four firms, however, the half-life estimates seem very high (seven days or more). Three of these four firms correspond to companies that display very low volume, and thus, arbitrage might be difficult to execute. The average half-life is 3.1 business days and the median half-life is 1.08 days. By allowing non-linear adjustments, the average half-life and the median half-life are reduced by more than 50%, when compared to the standard linear model.

This paper is organized as follows. Section II presents a brief literature review. Section III motivates the STAR model and briefly discusses estimation and testing issues. Section IV presents the data. Section V estimates the non-linear model and analyzes the conversion path to arbitrage parity. Section VI concludes the paper.

II. Literature Review

There is a growing body of literature that studies the potential arbitrage opportunities that cross-listed shares create. If prices between the local shares and their cross-listed shares differ substantially, arbitrage opportunities will arise. As pointed out in the introduction, the early studies conclude that arbitrage opportunities are non-existent for cross-listed shares and thus cross-listed shares are priced according to arbitrage parity. The only early study that did find some arbitrage opportunities is by Wahab, Lashgari and Cohn (1992). Some recent works, however, have found a significant deviation from arbitrage price parity. Froot and Dabora (1999), studying the pricing of two dual-listed companies, Royal Dutch and Shell, and Unilever N.V. and Unilever PLC, find a large and significant price deviation from arbitrage parity. Gagnon and Karolyi (2003) quantify sizable price deviations from arbitrage-free pricing between ADRs and their underlying assets. Gagnon and Karolyi (2003) document the existence of large price deviations for many of the 581 ADR-underlying pairs they study. They estimate discounts of up to 87% and premia of up to 66%. Gagnon and Karolyi (2003), after taking into account direct and indirect transaction costs still find the price deviations to be exceeding reasonable measures of transaction costs. Still, they mention that the complexity of rules in the ADR-underlying arbitrage precludes definite conclusions about potential market inefficiencies.

Large price deviations from arbitrage-price parity do not necessarily imply arbitrage profits are possible. Transaction costs, capital control restrictions, conversion rules, and lack of liquidity might make arbitrage very difficult. De Jong et al.(2003) and Hong and Susmel (2003) attempt to construct realistic arbitrage strategies to see whether arbitrage is possible. De Jong et al. (2003) extend the sample to 13 dual-listed companies and show that for every individual dual-listed company, deviations from arbitrage price parity are large. They design investment strategies for exploiting these deviations from price parity. They find that some arbitrage strategies in all dual-listed companies produce excess returns of up to 10% per annum on a risk-adjusted basis, after transaction costs and margin requirements. Hong and Susmel (2003) study simple arbitrage profits for ADR-underlying pairs. They find that pairs-trading strategies deliver significant profits. The results are robust to different profit measures and different holding periods. For example, for a conservative investor willing to wait for a one-year period, before closing the portfolio pairs-trading positions, pairs-trading delivers annualized profits over 33%. Suarez (2005a), using intradaily data for French ADR-underlying pairs, shows that large deviations from the law of one price are present in the data and that an arbitrage rule can be designed to exploit the large deviation from price parity.

A related line of research deals with the price discovery process. Eun and Sabberwal (2003) apply a standard linear error correction model to study price discovery shares for 62 Canadian shares cross-listed in the NYSE. They find a significant price deviation from arbitrage parity. They find that the price adjustments of U.S. prices to deviation from Canadian prices are significantly larger in absolute value. They also find that trading volume in the U.S. is the most important variable in the determination of relative information contribution of the two markets. Using intradaily data and a similar methodology, but for only three German firms, Gramming, Melvin, and Schlag (2001) find that the majority of the price discovery is done at home (Germany), but following a shock to the exchange rate, almost all of the adjustment comes through the New York price. A similar model, but using non-linear adjustment dynamics, is estimated by Rabinovitch et al. (2003). Using a non-linear threshold model for 20 Chilean and Argentine cross-listed stocks, Rabinovitch et al. (2003) estimate transactions costs and show that transaction costs play an important role in the convergence of prices of ADRs and their underlying securities. They find that capital control measures and liquidity significantly affect the price adjustment process, through increasing transactions costs. Melvin (2003) and Auguste et al. (2004) also find that capital movement restrictions can seriously affect the arbitrage price parity, especially during economic and currency crisis.

III. Non-linear convergence and Arbitrage Models

Let $P_t(A)$ represent the price of ADRs and $P_t(L)$ the price of underlying (locally) traded shares a time t. The relationship between both prices, under the arbitrage-free condition, with absence of transaction costs is specified as:

$$P_t(A) = B\, S_t\, P_t(L), \tag{1}$$

where S_t denotes the nominal exchange rate at time t, and B the bundling price ratio. Equation (1), price parity, is usually expressed in log form. The deviations from log price parity, q_t is given by

$$q_t \equiv p_t^L - p_t^A + s_t + b\,, \tag{2}$$

where small letters represents the log form of the above defined variables. Let κ measure the transaction costs, as a percentage, faced by arbitrageurs. Provided that κ is small, arbitrage will occur when:

$$| q_t | > \kappa \tag{3}$$

The dynamic behavior of q_t, the deviation from price parity between the ADRs and their underlying shares, has been mostly analyzed in a linear framework.[3] For example, Eun

[3] Exceptions are in Rabinovitch et al. (2003), Chung, Ho and Wei (2005) and Suarez (2005b), where threshold autoregressive models are used.

and Sabherwal (2003) use a standard error correction model. This linear framework is counterintuitive since, once arbitrage is triggered, arbitrage opportunities may disappear very slowly and always at the same speed. One way to address this issue is to consider that, under certain conditions, price differences should converge faster to price parity. This can happen when the convergence dynamics are governed by a nonlinear process. We start by assuming that small deviations from arbitrage-free prices between ADRs and their underlying shares may be considered negligible to generate arbitrage activities, notably when transactions and other related trading costs are not covered by the deviation from price parity. In this case, the deviation from price parity would behave as a near unit root process and would not converge to parity in a linear framework. On the other hand, when deviations from price parity are large, arbitrage activities, then, will create a reversion to the long-run equilibrium price parity. As the ADR-underlying pair moves further away from arbitrage parity, or long run equilibrium, arbitrage activities will likely increase.[4] Therefore, the dynamics of convergence to price parity should be influenced by the size of the deviation from price parity.

III.1 Modeling Nonlinear Adjustments

A model that captures this nonlinear adjustment process is the smooth transition autoregressive (STAR) model studied by Granger and Teräsvirta (1993) and Teräsvirta (1994).[5] The STAR model also displays regimes, but the transitions between regimes

[4] See Dumas (1992), Uppal (1993), Sercu et al. (1995), Coleman (1995), Obstfeld and Taylor (1997). These articles find that market frictions create an inactive transaction band, where small deviations from purchasing power parity prevent the real exchange rate to mean revert. Arbitrage opportunities exist only for large deviations outside the inactive band. Traders have a tendency to postpone entering the market until enormous arbitrage opportunities open up.

[5] Another popular nonlinear specification is the threshold autoregressive (TAR) model in which regime

occur gradually. In the STAR literature, the Exponential STAR (ESTAR) and the Logistic STAR (LSTAR) are the most popular models used for symmetric and asymmetric adjustments, respectively. The adjustment structure of both models depends on the magnitude of the departure of the underlying process from its equilibrium. A STAR model of order p for the univariate time series q_t can be formulated as:

$$q_t = \Psi_1^{'} x_t + \Psi_2^{'} x_t \Phi(z_t; \lambda, \mu) \ + \varepsilon_t, \quad \lambda > 0 \tag{4}$$

or

$$q_t = \mu + \sum_{j=1}^{p} \Psi_{1j} L^j (q_t - \mu) + \left[\sum_{j=1}^{p} \Psi_{2j} L^j (q_t - \mu) \right] [\, \Phi(z_t; \lambda, \mu) \,] + \varepsilon_t, \quad \lambda > 0 \tag{4'}$$

where the error term, ε_t, follows an identical and independent distribution, with zero mean and constant variance σ^2. The independent variable x_t is defined as $x_t = (1, \tilde{x}_t)'$ with $\tilde{x}_t = (q_{t-1}, q_{t-2}, \ldots, q_{t-p})'$ and $\Psi_i = (\Psi_{i0}, \Psi_{i1}, \ldots, \Psi_{ip})$, i =1,2, denotes the autoregressive parameters vector of dimension p of an AR(p); L is the lag operator; $\Phi(z_t; \lambda, \mu)$ is the smooth transition function, which determines the degree of convergence. The ESTAR model uses the exponential function as the transition function[6]:

$$\Phi(z_t; \lambda, \mu) \ = 1 - \exp\left\{ -\lambda (z_t - \mu)^2 / \hat{\sigma}_{z_t}^2 \right\}, \quad \lambda > 0 \tag{5}$$

where, z_t, the transition variable is assumed to be a lagged endogenous variable $z_t = q_{t-d}$ for which d is the delay lag, a nonzero integer (d > 0), that determines the lagged time

changes occur abruptly, see Tong (1990). A problem with this approach is that the model has two very distinct regimes: outside the threshold (where arbitrage happens) and inside the threshold (where there is no arbitrage). The change from one regime to the other is abrupt and it presumes the same speed of adjustment outside the threshold. The LSTAR model contains as a special case the single-threshold TAR model, discussed in this section.

[6] The sample variance of the transition variable is used to scale the argument of the exponential as suggested by Granger and Teräsvirta (1993, p.124). The scaling enables a stability improvement of the nonlinear least squares estimation algorithm, a fast convergence, and an interpretation and comparison of λ estimates across equations in a scale-free environment.

between a shock and the response by the process, the parameter λ determines the speed of transition between regimes, and μ can be interpreted as the arbitrage parity, equilibrium level. Note that, for a given price parity deviation, lower (higher) values of λ determine slower (faster) values for Φ(.) and, thus, slower regime transitions.

The transition function is symmetrical around the equilibrium level (mean). Substituting (5) into (6), the ESTAR model can be written as:

$$q_t = \mu + \sum_{j=1}^{p} \Psi_{1j} L^j (q_t - \mu) + \left[\sum_{j=1}^{p} \Psi_{2j} L^j (q_t - \mu) \right] [1 - \exp\{-\lambda (z_t - \mu)^2 / \hat{\sigma}_{z_t}^2\}] + \varepsilon_t \quad (6)$$

$$\text{or} \quad q_t = \Psi_1' x_t + \Psi_2' x_t \; [1 - \exp\{-\lambda (z_t - \mu)^2 / \hat{\sigma}_{z_t}^2\}] + \varepsilon_t \quad (6')$$

The transition function is bounded between zero and one. The inner regime is characterized by $q_{t-d} = \mu$, when Φ(.) = 0. The ESTAR model (6) then degenerates to a standard linear AR (p):

$$q_t = \mu + \sum_{j=1}^{p} \Psi_j L^j (q_t - \mu) + \varepsilon_t. \quad (7)$$

The outer regime is characterized by an extreme deviation from the price parity, when Φ(.) = 1, in which case model (6) converts to a different AR(p) representation:

$$q_t = \mu + \sum_{j=1}^{p} (\Psi_{1j} + \Psi_{2j}) L^j (q_t - \mu) + \varepsilon_t. \quad (8)$$

The model displays global stability provided $\sum_{j=1}^{p} (\Psi_{1j} + \Psi_{2j}) < 1$, although it is possible that $\sum_{j=1}^{p} \Psi_j \geq 1$ implying then q_t may follow a unit root process or even explodes around the arbitrage free parity level.

The LSTAR model uses the logistic function, instead of an exponential function, to model the transition function $\Phi(.)$. Thus, after substituting in (4'), the LSTAR model can be written as:

$$q_t = \Psi_1' x_t + \Psi_2' x_t \ \ [1/(1+\exp\{-\lambda(z_t - \mu)/\hat{\sigma}_{z_t}\})] + \varepsilon_t, \quad \lambda > 0.$$

III.2 Estimation, Testing and Model Selection[7]

Following Teräsvirta (1994), the starting point in modeling a STAR specification consists of an adequate choice of the autoregressive parameter, p, and of the delay parameter, d. Second, a sequence of tests of the null hypothesis of linearity (AR model) is performed, along with other diagnostic tests. Third, if the null hypothesis of linearity is rejected, the model is specified as ESTAR or LSTAR. The choice of ESTAR or LSTAR model is based on a comparison of p-values for a sequence of LM tests.[8]

The choice of the autoregressive parameter, p, is based on the Akaike information criterion (AIC). However, the AIC tends to under-parameterize an AR model. Thus, we also look at the partial autocorrelation function (PACF) using a 95% confidence interval band. In order to specify the delay parameter, d, a sequence of linearity tests is carried out for different ranges of d with $1 \leq d \leq D$ considered appropriate. If the null hypothesis of linearity is rejected at a pre-specified level for more than one value of d, then d is determined at $d = d^*$ such that: $d^* = \text{Arg}\{\text{Min } p(d)\}$ for $1 \leq d \leq D$, where p(d) denotes the (p-value) of the selected test. The correct choice of d is important for the test to have a maximum power. For this paper, we set the maximum value of d equal to 5 business days as it seems unreasonable to argue that it would take more than 5 days for the price

[7] See the Appendix for details.
[8] See Van Dijk et al. (2002) for a survey of the different modeling procedures for STAR models.

spread to start adjusting if there is an arbitrage activity. Once p and d are selected, estimation of a STAR model can be straightforward using non-linear least squares.

We test for the presence of nonlinearity in the price spread between the local assets and their corresponding ADRs using the Lagrange Multiplier (LM) tests proposed by Luukkonen et al.(1988); Granger and Teräsvirta (1993) and Teräsvirta (1994) (hereafter, the TP procedure); and Escribano and Jordá (1999) (hereafter, the EJP procedure). For each test, we conduct a heteroskedasticity-consistent specification since neglecting heteroskedasticity can seriously affect the power of LM tests, see Wooldridge (1990, 1991).[9]

Once a nonlinear specification is found adequate, the next task is to choose between the ESTAR and the LSTAR models. Teräsvirta (1994) suggests the following model selection procedure. Let LM^{EST} denote the F-test of the ESTAR null hypothesis, and let LM^{LST} denote the F-test of the LSTAR null hypothesis. The relative strength of the rejection of each hypothesis is then compared. If the minimum p-value corresponds to LM^{LST}, the LSTAR model is selected, but if it corresponds to LM^{EST}, the selected model is the ESTAR.

IV. The Data

The data analyzed in this paper are the daily prices on twenty one locally traded firms from Mexico, obtained from Datastream. To be part of our sample, the ADR has to

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[9] Van Dijk et al. (1999) develop outliers-robuts tests, since they show that in the presence of additive outliers, LM tests for STAR nonlinearity tend to incorrectly reject the null hypothesis of linearity. We used such tests along with the heteroskedasticity tests, but there were no major changes for our sample.

be Level III or Level II. The sample periods are different for the different firms, depending on the dates for which ADRs started trading on these firms on the U.S. market.

Table 1 presents the twenty one firms and the sample period for each of them. Table 2 exhibits several statistics for each firm: Market Capitalization (MC), average daily volume since inception (Volume), the number of freely traded shares in the hands of the public (Float), and the short-ratio, which is calculated as the short interest for the current month divided by the average daily volume. In the last four columns of Table 2, we also present summary statistics for the deviations from price parity (in %):

$$Q_t = (B\ S_t\ P_t(L)/\ P_t(A) - 1)*100.$$

Analyzing the statistics for Q_t, we observe evidence for autocorrelation. We also tend to observe a negative relation between liquidity and departure from theoretical price parity: the less liquid a stock is, the bigger the departures from price parity, as shown by the mean and maximum and minimum statistics.

V. Results

The lag selection is based on both the AIC and the partial autocorrelation functions (PACF). Figure 1 displays the PACF for selected firms with a 95% confidence interval band. It indicates that for most series, only the first or second autocorrelation coefficients are significant at the 5% level. Therefore, the maximum AR used is 2, which seems to purge the residuals series from serial correlation. As a check, we also estimate models with $p>3$, with $d=\{1,2,\ldots,10\}$, to test for a higher AR order in q_t; but the results are very similar to the ones presented below.

Table 3 reports p-values for the standard and heteroskedasticity-consistent test statistics NLM3 and NLM4 for testing the linearity hypothesis. Table 3 also reports test statistics NLM2 (an LM^{EST} test), LM^{LST} and LM^{EST} for choosing between ESTAR and LSTAR (see Appendix for details). Panel A shows all the test results for one firm, TMX.[10] Panel B shows a summary of the test results for all the other firms. The second column of Table 3 displays the different values for the delay parameter, d = {1,2,…,5}.[11] Using the results on the first panel of Table 3 for TMX, we select d=2, as the results indicate the smallest p-values (corresponding to NLM3 and NLM4) for both tests; that is, for d=2 we obtain the strongest rejection of the AR linear hypothesis. Also, for d=2, the ESTAR model is selected over the LSTAR model since the p-value of the LM^{EST} test is smaller than the p-value of the LM^{LST} test, for both versions of the test. Note that the p-value of the NLM2 test confirms this selection. We follow this process for the other firms. Based on the standard LM test statistics NLM3 and NLM4, reported in Panel B, of Table 3 for all the firms, the null hypothesis of linearity can be rejected for any values of d and corresponding transition variables, at the 1% level. For the majority of the firms, we select d=1, that is, yesterday's deviation from price parity. When we use the heteroskedasticity-consistent robust tests, the null hypothesis of linearity is still rejected for the majority of the firms. Using the NLM3 test, and the lag selected by the standard

[10] The results for the other firms can be reported similarly, but are not included to save space. They are available under request.

[11] The tests are performed with values of the delay parameter, d ={1,2,…,10}, yet we report the tests statistics for d={1,2,…,5} since d={6,…,10} do not alter the choice of d and are less relevant for the convergence of a daily price spread series. We also used as the transition variable, z_t, the first lag of the average absolute volatility, $v_{t,k}$ as suggested by LeBaron (1992) as: $v_{t,k} = \frac{1}{k}\sum_{i=0}^{k-1} |q_{t-i}|$, where k is the number of days, with a maximum of 5 business days. The tests selected $v_{t,k}$ as adequate transition variables for six stocks. Overall, our results are unchanged.

homoscedastic test, we find eighteen firms with a p-value lower than 10%. For example, for FMX the results of the heteroskedasticity-robust test indicate that the transition variables zt $=q_{t-1}$, q_{t-2}, and $v_{t-1,4}$ are adequate transition variables, since the corresponding p-values are smaller than .10. The NLM3 test, for q_{t-1}, rejects linearity, showing a p-value of .072. The results from the NLM4 test statistic, computed using the Escribano and Jordá test, confirm the NLM3 selection. Finally, the p-values of the LM statistics (standard or heteroskedasticity-consistent) NLM2 suggest an ESTAR model is the more appropriate model. Comparing relative strength of the tests LM^{EST} and LM^{LST}, the minimum p-values correspond to LM^{EST}, indicating a choice in favor of the ESTAR model. In most cases, the LM^{EST} is significant at the 5% level for d=1. Thus, based on the decision rules of Teräsvirta (1994), the ESTAR model with a delay, d=1 should be an adequate model specification for FMX return spread. We carry on an identical evaluation for the other firms. With few exceptions we find the ESTAR to be the most adequate model.

V.I Nonlinear Estimation Results

Following Gallant and White (1988), the resulting ESTAR(p) models, with p={1,2}, are estimated by nonlinear least squares. We test the following restrictions consistent with the application of ESTAR specifications to arbitrage models, $\Psi_{11} + \Psi_{12} = 1$, $\Psi_j = -\Psi_j$ (j=1,2), and $\mu = 0$. Under the first restriction, the model behaves like a random walk, and thus there is no convergence to equilibrium, when the transition function is equal to 0 (no arbitrage regime). Under the second set of restrictions, $\Psi_j = -\Psi_j$ (j=1,2), there is full convergence to price parity when the transition function is equal to 1 (full arbitrage regime). The last restriction, $\mu = 0$, implies that the equilibrium price parity deviation is zero. The restrictions are tested using likelihood ratio tests. If all the restrictions cannot be rejected, and if imposed, the final model is governed by λ, the speed of transition between regimes. When the last restriction cannot be rejected, we impose it and we re-estimate the model. The model estimates, the likelihood ratio, and residuals diagnostic statistics are presented in Table 4. In column ten, we report the p-value associated with the likelihood ratio statistic, LR(k). The LR(k) statistics show that at least one of the restrictions cannot be rejected at the standard 5% level for all series. The number of restrictions that cannot be rejected varies from one firm to another. For example for the firm AMX, the p-value of LR(4) is 0.561, thus, we failed to reject four restrictions.[12] The failure to reject the first two restrictions for AMX indicate that when the transition function is equal to zero (no arbitrage regime) there is no tendency to converge to price parity; on the other hand, when the transition function is equal to one (full arbitrage regime) there is full convergence to price parity. Overall, this type of dynamic adjustment for deviations from price parity is the usual for all the firms. That is, we find that for small deviation from price parity there is no tendency for reversion towards price parity; while for large deviations from price parity there is a full reversion to price parity. The restriction $\mu = 0$ cannot be rejected for the majority of the firms, that is, the long-run deviation from price parity is zero. In the fourth column of Table 4, we report the estimated λs, the transition parameters. With only one exception, TMM, the estimates of λ are all significantly different than zero.[13] The size of λ changes from 2.971

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[12] $\Psi_{11}+\Psi_{12,}= 1$, $\Psi_{21} = -\Psi_{11}$, and $\Psi_{22} = -\Psi_{12}$, and $\mu = 0$.

[13] Taylor et al. (2001) point out that the significance of λ estimate based on individual t-ratios should be checked for robustness. Technical problems emerge under the null hypothesis that $\lambda = 0$.

to 0.315. It is worth noticing that firms with a higher estimate of λ tend to have higher average daily volume and market capitalization. Whereas firms for which the price spread series exhibits a lower speed of adjustment coefficients, such as ICM (λ=0.317), GMK (λ=0.361), and TMM (λ=0.315), tend to have lower average daily volume and market capitalization. Overall, the estimated values reported in Table 4 support a nonlinear dynamic convergence of the price spread series towards price parity.

We also conduct specification tests for our ESTAR model. The residuals diagnostic statistics for the estimated equations are reported in the last two columns of Table 4. Following Eitrheim and Teräsvirta (1996), we calculate LMNA and NL_{Max}. LMNA AR(1-6) is a LM-test statistics for testing the null hypothesis of no serial correlation in the residuals of order 1, up to 6. NL_{Max} represents the maximum LM-test statistic of no additive nonlinearity with the delay length in the range from 3 to 6. The associated p-values indicate that we cannot reject those null hypotheses for all firms at the 5% level or better. Therefore, an ESTAR specification seems adequate for the price spread series.

V.II Estimated Transition Functions

The transition function measures the magnitude of deviations of the price spread from its arbitrage-free level. The estimates of the transition functions are shown on Figure 2 for selected stocks; they are plotted against the transition variable, q_{t-d}, (Panel A) and against time (Panel B). These figures visually support the nonlinear nature of the price spread series and the appropriateness of the ESTAR model, since, in general, observations seem to symmetrically lie above and below the parity. Again, we notice a relation between slow convergence and liquidity.[14] For example, in Panel A, for a firm with a good daily volume like KOF, a previous day's deviation from parity of the order plus or minus 2%, the transition function attains smaller values (0.5), implying a relatively slow mean reversion, whereas for a larger previous day's deviation around 4%, the transition function reaches the value of 1, the regime of full arbitrage, signaling a faster reversion. On the other hand, for a firm with a low daily volume TMM, a 30% spread makes the transition function equal to .5. In general, most of the transition functions in Panel A indicate that deviations lower than 5% trigger a full arbitrage regime. Panel B shows that for some firms, there are few days of full arbitrage --i.e., when the transition function is equal to 1--, while for others, there are many days of full arbitrage. Again, there seems to be a positive relation between low volume and number of days under the full arbitrage regime.

V.III Half-lives and Convergence to Parity

While both estimated ESTAR models and transition functions shed lights on the nonlinear nature of the reversion of the price spread to parity, more insights into the adjustment mechanism of the models can be gained by estimating the average time it takes for a given shock to die out, also called the speed of convergence to parity. As a measure of the speed of convergence, we calculate the half-life of a shock, defined as the number of periods it takes for shocks to the price spread to dissipate by half. Following

[14] We included lagged changes in volume in the transition function, but the model did not perform better than our model.

Taylor and Peel (2000) and Taylor et al. (2001), we estimated the half-lives for shocks using the generalized impulse response function (GIRF).[15]

The half-life is defined in a non-linear framework as the number of periods taken by the impulse response function to fall below 0.5 δ, or GIRF < 0.5 δ, with $\delta = \ln(1+\frac{k}{100})$, where k represents the percentage of shocks. Alternatively, to mitigate differences in GIRF due to the different variability of the underlying series, shocks can be set as $\delta = c\,\hat{\sigma}_\varepsilon$ where $\hat{\sigma}_\varepsilon$ denotes the residual standard deviations and c is a scalar. We use this formulation to calculate half-lives. We estimate the half-lives for all price spread series for three sizes of shocks**:** $1\hat{\sigma}_\varepsilon$ $3\hat{\sigma}_\varepsilon$ and $5\hat{\sigma}_\varepsilon$. For comparison purposes, we also compute half-lives for a linear adjustment.

In the second to fourth columns of Table 5, we report the estimated half-lives for all firms, using the ESTAR model, for three different sizes of shocks. In the last column, we also report the half-life estimates for the standard AR linear adjustment model. All half-life estimates are expressed in business days. From the non-linear estimation, we observe faster adjustments for the majority of firms. The half-life estimates are similar across shock sizes. A larger shock to the price spread triggers a faster reversion to parity. For the non-linear model, using one residual standard deviation as the shock, the average half-life is 3.1 business days, a reduction of more than half when compared to an average half-life for the linear model of 7.26 business days. That is, we observe for all firms a significant reduction in the half-life estimates when nonlinearities are incorporated into

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[15] Following Koop et al. (1996), the generalized impulse response function is defined as the difference between two conditional first moments:

$GIRF_x(j, s_t, \omega_{t-1}) = E[X_{t+j} | s_t, \omega_{t-1}] - E[X_{t+j} | \omega_{t-1}]$, j=1,2,…,N,

where E[.] denotes the expectation operator, j is the forecasting horizon, s_t is the perturbation of the system at time t, $h_t \equiv \omega_{t-1}$ represents the conditioning information set at time t-1 consisting of the history or initial conditions of the variable. $GIRF_x(j, s_t, \omega_{t-1})$ is computed using a dynamic stochastic simulation. See also the arbitrage model. These averages, however, are influenced by a few large observations. The non-linear half-life median is 1.08 business days, also a reduction of more than half when compared to the median half-life for the linear model of 2.29 business days. These nonlinear results are in line with the findings of Gagnon and Karolyi (2003), where the average deviation from price parity can persist for up to five days. Note that for 14 out of 21 firms, using the nonlinear model, it takes less than two day for the ADR-underlying price spread to be reduced by half. The size of the shock to price parity also matters, for 17 firms the half-life is reduced to less than 2.3 days if the shock size is five times the residual standard deviation. Again, these results seem consistent with the discussion in Gagnon and Karolyi (2003), where it is mentioned that although the process of issuance and cancellation of ADRs can take place on the same day, it usually occurs on an overnight basis.

Some of the high half-life estimates correspond to companies that display very low volume (CDG, ICM, TMM).[16] This finding is similar to the results reported in Rabinovitch et al. (2003), where low volume is associated with higher transaction costs, and in Roll, Schwartz, and Subrahmanyam (2004), where liquidity and lack of arbitrage opportunities are positively related.

V.IV Nonparametric Tests of Association between Liquidity and Convergence

To formally explore whether popular indicators of a firm's liquidity such as daily volume, market capitalization, and float are correlated with a firm's convergence to price

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Peel and Venetis (2003a, 2003b) for a similar application to measure the half-lives of real exchange rates.

[16] ICA, the other firm with a high half-life estimate, is seriously affected by a significant change in the premium after December 3, 2003. The average premium changed from 27% to 3%. Besides a significant investment by Mexican investor Carlos Slim, we could not find any information as to why ICA shows such

parity, a nonparametric Spearman rank correlation test is conducted. The null hypothesis is that a firm' liquidity characteristics are not related to the speed of transition between regimes or the speed of convergence to parity against the alternative of them being associated.

Table 6.A shows the raking of firms' liquidity indicators, while Table 6.B shows the Spearman rank correlations. For the non-linear adjustment model, the results indicate that the null hypothesis of no association can be rejected at the 5% level for all liquidity characteristics. The average daily volume, market capitalization, and float are all positively and significantly correlated to the half-life and the speed of transition between regimes calculated using our non-linear estimators. Our non-linear estimates provide a better measure of liquidity than the standard linear estimates. The estimated correlations using the non-linear half-life estimates are substantially higher than the estimated correlations using the linear half-life estimates. For example, the correlations between market capitalization, average daily volume and float and the non-linear half-life estimates are .83, .58, and .66, respectively, while the correlation between the same liquidity indicators and the linear half-life estimates are .70, .40, and .51, respectively.

VI. Conclusions

In this paper we study the convergence between the prices of ADRs and the prices of the Mexican traded shares. We have a sample of 21 dually listed shares (listed in Mexico and in the U.S.), that are listed as level II or level III ADRs. Since both markets have similar trading hours, standard arbitrage considerations should make persistent deviation from price parity rare. We estimate two different non-linear adjustment models,

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a significant change in premium. ICA's half-life estimates before and after December 3, 2003 are inline the LSTAR and ESTAR models, along with a standard linear model to estimate the convergence of the ADRs and the locally traded shares. From our estimation results, first, we reject the linear adjustment model; and, second, based on different tests, we select the ESTAR model. Overall, we find that for small deviation from price parity there is no tendency for convergence towards price parity; while for large deviations from price parity there is a full reversion to price parity. Using the ESTAR model, we are able to estimate the half-life of different shocks to price spreads. We find that price spreads tend to die out quickly in a nonlinear framework. The sample average half-life is 3.1 business days, while the median half-life is 1.08 business days. By allowing non-linear adjustments, the average half-life is reduced by more than 57%, when compared to the standard linear model. For 14 out of 21 firms it takes less than 2 days for the ADR-underlying price spread to be reduced by half. Four firms, however, have high half-life estimates (seven days or more), and, in general, correspond to companies that display very low volume, and thus, arbitrage might be difficult to execute. The results of a Spearman correlation tests confirm this finding, as most firm's liquidity market indicators are positively correlated to the speed of convergence to parity. The size of the shock to price parity also matters, for 17 out of 21 firms the half-life is reduced to less than 2.3 days when the shock size is five times the residual standard deviation.

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with the rest of the firms.

References

Auguste, S., K. Dominguez, H. Kamil and L. Tesar, (2004), "Cross-Border Trading as a Mechanism for Capital Flight: ADRs and the Argentine Crisis," University of Michigan working paper.

Barberis, N. and R. Thaler, (2002), A survey of behavioral finance, forthcoming in G. Constantindes, M. Harris and R. Stulz, eds., Handbook of the Economics of Finance.

Coleman, A.M. (1995), "Arbitrage, Storage and the "Law Of One Price"; Mimeo, Princeton University.

Chung, H., Ho, T. W. and L.J. Wei (2005)," The dynamic relationship between the prices of ADRs and their underlying stocks: evidence from the threshold vector error correction model," Applied Economics; 37, 2387 – 2394.

De Jong, A., L. Rosenthal, and M. van Dijk, (2003), "The limits of arbitrage: Evidence from dual-listed companies," Erasmus University working paper.

Dickey, D. A. and W. A. Fuller, (1979) "Distribution Of The Estimators For Autoregressive Time Series with A Unit Root," Journal of the American Statistical Association 74, 427-431.

Domowitz, I., J. Glen and A., Madhavan (1997b), "Market segmentation and Stock Prices: Evidence from an Emerging Market," The Journal of Finance, 52, 1059 – 1085.

Dumas, B., 1992, "Dynamic Equilibrium and the Real Exchange Rate in a Spatially Separated World," Review of Financial Studies, 8, 709-742.

Dwyer, G., Locke, P., and Yu, W., (1996), "Index arbitrage and non-linear dynamics between the S&P500 futures and cash," Review of Financial Studies, 9, 301-332.

Escribano, A. and Jordá, O. (1999), "Improved Testing and Specification of Smooth Transition Regression Models," in **Nonlinear Time Series Analysis of Economic and Financial Data,** Rothman, P., Kluwer: Boston, 289-319.

Eun, C. and S. Sabberwal (2002) "Cross-border listing and price discovery: Evidence from U.S. listed Canadian stocks," Journal of Finance 58, 549-577.

Froot, K. A. and E. Dabora, (1999) "How are Stock Prices Affected by the Location of Trade?," Journal of Financial Economics 53, 189-216.

Gagnon, L. and G. A. Karolyi, (2003), "Multi-market Trading and Arbitrage," unpublished manuscript.

Grammig, J., M. Melvin, and C. Schlag, (2001) “Internationally cross-listed stock prices during overlapping trading hours: Price discovery and exchange rate effects,” Working Paper, Arizona State University.

Granger, C.W.J. and Terasvirta, T (1993), “Modeling nonlinear economic relationships,” Oxford University Press. Oxford, U.K.

Hong, G. and R. Susmel, (2003), “Pairs-Trading in the Asian ADR Market,” University of Houston, unpublished manuscript.

Kato, K., S. Linn, and J. Schallheim, (1991), “Are There Arbitrage Opportunities in the Market for American Depository Receipts?” Journal of International Financial Markets, Institutions & Money 1, 73-89.

Karolyi, G. A., (1998), “Why do companies list shares abroad?: A survey of the evidence and its managerial implications,” Financial Markets, Institutions, and Instruments Vol. 7, Blackwell Publishers, Boston.

Karolyi, G. A., (2004), “The World of Cross-Listings and Cross-Listings of the World: Challenging Conventional Wisdom,” Ohio State University, unpublished manuscript.

Koumkwa, F. Samuel (2004), “Nonlinear Dynamic Adjustment of Real Exchange Rates in Emerging Markets,” (Working Paper, University of Houston, Dept. Finance)

Koop, G., M. H. Pesaran, and S. M. Potter, (1996), “Impulse Response Analysis in Non-Linear Multivariate Models,” Journal of Econometrics, 74, 119-147.

LeBaron, B. (1992), “Do moving average trading rule results imply nonlinearities in foreign exchange markets?,” working paper, University of Wisconsin - Madison, Madison, Wisconsin.

Lukkonnen, R., P. Saikkonen, and T. Terarsvirta, (1988), “Testing linearity against smooth transition autoregressive models,” Biometrika, 75, 239-266.

Maldonado, W. and A. Saunders, (1983), “Foreign exchange futures and the law of one price,” Financial Management, 12, 19-23.

Melvin, M., (2003), “A Stock Market Boom During a Financial Crisis: ADRs and Capital Outflows in Argentina,” Economics Letters 81, 129-136.

Miller, P. D., and R. M. Morey, (1996), “The Intraday Pricing Behavior of International Dually Listed Securities,” Journal of International Financial Markets, Institutions and Money, 6, 79-89.

Mullainathan, S. and R. Thaler, (2000) “Behavioral economics,” MIT working paper.

Obstfeld, M. and M. Taylor (1997), "Nonlinear Aspects of Goods-Market Arbitrage and Adjustment: Hecsher's Commodity Points Revisited," Journal of Japanese and International Economics, 441-479.

O'Connell, Paul and Shang-Jin Wei (1997); "The Bigger They Are, The Harder They Fall"; NBER Working Paper No. 6089, July.

Park, J., and A. Tavokkol, (1994), "Are ADRs a Dollar Translation of Their Underlying Securities? The Case of Japanese ADRs," Journal of International Financial Markets, Institutions, and Money 4, 77-87.

Peel, D.A., and I. A. Venetis, (2003a), "Smooth transition models and arbitrage consistency," Economica.

Peel, D.A., and I. A. Venetis, (2003b), "Purchasing Power Parity over Two Centuries: Trends and Non-linearity", Applied Economics.

Rabinovitch, R., A. C. Silva and R. Susmel (2003) "Returns on ADRs and Arbitrage in Emerging Markets," Emerging Markets Review, Vol. 4, 225-328.

Rosenthal, L. and C. Young (1990), "The Seemingly Anomalous Price Behavior of Royal Dutch/Shell and Unilever N.V./PLC," Journal of Financial Economics 26, 123-41.

Roll, R., E. Schwartz, and A. Subrahmanyam, (2004), "Liquidity and Arbitrage," UCLA, working paper

Sercu, P., R. Uppal and C. Van Hulle, (1995), "The Exchange Rate in the Presence of Transactions Costs: Implications for Tests of Purchasing Power Parity," Journal of Finance, 50, 1309-1319.

Suarez, E. D., (2005a), "Arbitrage opportunities in the depositary receipts market: Myth or reality?," Journal of International Financial Markets, Institutions and Money, 15,469-480.

Suarez, E. D., (2005b), "Enforcing the Law of One Price: Nonlinear Mean Reversion in the ADR Market," 31, 1-17.

Stulz, M. R., (1981), "On the Effects of Barriers to International Asset Pricing," Journal of Finance, 25, 783-794.

Stulz M. R. and W. Wasserfallen, (1995), "Foreign Equity Investment Restrictions, Capital Flight and Shareholder Wealth Maximization: Theory and Evidence," The Review of Financial Studies, 8, 1019 – 1058.

Taylor, N., D. van Dijk, P. Franses, and A. Lucas, (2000), "SETS, arbitrage activity, and stock price dynamics," Journal of Banking & Finance, 24, 1289-1306.

Taylor, M. P., and D. A. Peel (2000) “Nonlinear Adjustment, Long-run Equilibrium and Exchange Rate Fundamentals,” Journal of International Money and Finance, 19, 33-53.

Terasvirta, T. (1994), “Specification, Estimation, and Evaluation of Smooth Transition Autoregresive Models,” Journal of the American Statistical Association, 89, 208-218.

Tong, H., (1990), Threshold Models in Non-linear Time Series Analysis. Lecture Notes in Statistics, 21. Berlin: Springer.

Uppal, R., 1993, “A General Equilibrium Model of International Portfolio Choice,” Journal of Finance, 48, 529-553.

Van Dijk, D., T. Terasvirta, and P. H. Franses (2002), “Smooth Transition Autoregressive Models: A Survey of Recent Developments, Econometrics Review, 21, 1-47.

Wahab, M. and A. Khandwala, (1993), “Why Diversify Internationally With ADRs?,” Journal of Portfolio Management, 20, 75-82.

Wahab, M., M. Lashgari, and R. Cohn, (1992), “ Arbitrage in the American Depository Receipts Market Revisited,” Journal Of International Markets, Institutions and Money, 2, 97.

Woodridge, J. M., (1990), “A Unified Approach to Robust, Regression-Based Specification Tests,” Econometric Theory 6, 17-43.

Woodridge, J. M., (1991), “On the Application of Robust, Regression-Based Diagnostics to Models of Conditional Means and Conditional Variances,” Journal of Econometrics 47, 5-46, January 1991.

APPENDIX

A.I Testing and Estimation of STAR Models

We start by rewriting equation (4'):

$$q_t = \mu + \sum_{j=1}^{p} \Psi_{1j} L^j (q_t - \mu) + \left[\sum_{j=1}^{p} \Psi_{2j} L^j (q_t - \mu) \right] [\, \Phi(z_t; \lambda, \mu) \,] + \varepsilon_t, \quad \lambda > 0 \qquad (4')$$

Using equation (4'), we can test the null hypothesis of linearity, by testing H_0: $\Psi_2 = 0$ against the alternative hypothesis H_1: $\Psi_{2,j} \neq 0$ for at least one $j \in \{0,\ldots,p\}$. However, under the null, the transition function's parameters λ and μ are unidentified. Following Saikkonen and Luukkonen (1988a) and Teräsvirta (1994), a third order Taylor series expansion of the transition function $\Phi(q_t; \lambda, \mu)$ around zero is used to overcome non-identification issues. The re-parameterization of equation (4') yields the following artificial regression:

$$q_t = \beta_{00} + \sum_{j=1}^{p} \beta_{0j} q_{t-j} + \sum_{j=1}^{p} \beta_{1j} q_{t-j} q_{t-d} + \sum_{j=1}^{p} \beta_{2j} q_{t-j} q_{t-d}^2 + \sum_{j=1}^{p} \beta_{3j} q_{t-j} q_{t-d}^3 + \nu_t \qquad (A.1)$$

where $\beta_j = (\beta_{0j}, \beta_{1j}, \beta_{2j},\ldots, \beta_{pj})$ with j=1,2,3 are function of the AR coefficients vector $(\Psi_{i0}, \Psi_{i1},\ldots, \Psi_{ip})$, i =1,2 and the transition function parameters λ and μ. Thus, assuming d is known, the null hypothesis of the linearity test can be written as H_0: $[\beta_{1j} = \beta_{2j} = \beta_{3j} = 0]$, with $j=\{1,2,\ldots,p\}$. For large samples, the derived test statistic, NLM3, follows a χ^2 distribution with (p+1) degrees of freedom. We also use the non-linearity tests developed by Escribano and Jordá (1999) that account for the fourth power of the transition variable. This test tries to overcome the finding that when the variance of the error terms is large, the LSTAR (a nonlinear model) will be wrongly detected by the test more frequently. The underlying auxiliary regression is:

$$q_t = \beta_{00} + \sum_{j=1}^{p}\beta_{0j}q_{t-j} + \sum_{j=1}^{p}\beta_{1j}q_{t-j}q_{t-d} + \sum_{j=1}^{p}\beta_{2j}q_{t-j}q_{t-d}^{2} + \sum_{j=1}^{p}\beta_{3j}q_{t-j}q_{t-d}^{3} + $$

$$+ \sum_{j=1}^{p}\beta_{4j}q_{t-j}q_{t-d}^{4} \qquad \text{(A.2)}$$

The null hypothesis of linearity is then: H_0: $\beta_{1j} = \beta_{2j} = \beta_{3j} = \beta_{4j} = 0$, with j=1,…,p. The resulting test statistic, denoted NLM4, follows a chi-squared distribution with 4(p+1) degrees of freedom for large samples. The rejection of the null hypothesis will indicate the presence of nonlinearity.

A.II Model Selection: Testing ESTAR vs. LSTAR

Once a nonlinear specification is found adequate, the next task is to choose between the ESTAR and the LSTAR models. Teräsvirta (1994) suggests the use of the artificial regression (A.1) to perform a LM test of the ESTAR specification against the alternative of the LSTAR specification. In fact, the significance of cubic terms in equation (A.1) will not indicate the ESTAR adjustment in that the third order Taylor expansion of the transition function of an ESTAR model has a quadratic form (U-shape). The cubic terms will rather signal a LSTAR type of adjustment (asymmetry). In other words, the rejection of the null hypothesis H_{0L}: $\beta_{3j} = 0$ with j=1,…,p leads to the selection of the LSTAR model, whereas the rejection of the null hypothesis H_{0E}: $\beta_{2j} = 0 \mid \beta_{3j} = 0$ with j=1,…,p leads to the selection of the ESTAR model. The test NLM2 tests H_{0E}. Escribano and Jordá (1999) also develop a LM-type test to discriminate between LSTAR and ESTAR using the artificial Equation (A.2) and conditional on prior rejection of linearity. The selection procedure is as follow: Let LM^{EST} denote the F-test of the null hypothesis H_{0E}: $[\beta_{2j} = \beta_{4j} = 0]$ with j=1,…,p for ESTAR, and LM^{LST} the null hypothesis

H_{0L}: [$\beta_{1j} = \beta_{3j} = 0$] with j=1,…,p for LSTAR. The relative strength of the rejection of each hypothesis is then compared. If the minimum p-value corresponds to LM^{LST}, LSTAR is selected, if it rather corresponds to LM^{EST}, the select model is ESTAR.

TABLE 1: DATA DESCRIPTION

ADR ISSUE	SYMBOL	EXCHANGE	RATIO	INDUSTRY	TYPE	EFF.DATE
AMERICA MOVIL SA DE CV- SERIES 'L'	AMX	NYSE	1:20	Wireless Comm.	Level II	8-Feb-01
CEMEX S.A. DE CV	CX	NYSE	1:5	Building Materials	Level II	1-Sep-99
COCA-COLA FEMSA 'L' SHARES	KOF	NYSE	1:10	Beverage	Level III	1-Sep-93
CORPORACION DURANGO	CDG	NYSE	1:2	Forest Products & Paper	Level III	1-Jul-94
DESC, S.A. DE C.V.	DES	NYSE	1:20	Auto Parts & Tires	Level III	20-Jul-94
EMPRESAS ICA, S.A. DE C.V.	ICA	NYSE	1:6	Heavy Construction	Level III	1-Apr-92
FOMENTO ECONOMICO MEXICANO, S.A. DE C.V.	FMX	NYSE	1:10	Beverage	Level II	11-Feb-04
GRUMA, S.A. DE C.V. - 'B' SHARES	GMK	NYSE	1:4	Food	Level II	6-Nov-98
GRUPO AEROPORTUARIO DEL SURESTE	ASR	NYSE	1:10	Gen. Industrial Svcs	Level III	28-Sep-00
GRUPO IMSA	IMY	NYSE	1:9	Industrial Diversified	Level III	10-Dec-96
GRUPO INDUSTRIAL MASECA S.A. DE C.V.	MSK	NYSE	1:15	Food	Level II	17-May-94
GRUPO IUSACELL	CEL	NYSE	1:5	Wireless Comm.	Level II	5-Aug-99
GRUPO RADIO CENTRO, S.A. DE C.V.	RC	NYSE	1:9	Broadcasting	Level III	9-Jul-93
GRUPO SIMEC 'B' SHARES	SIM	AMEX	1:1	Mining & Metals	Level III	1-Jun-93
GRUPO TELEVISA, S.A.	TV	NYSE	1:20	Broadcasting	Level III	16-Sep-02
GRUPO TMM	TMM	NYSE	1:1	Industrial Transport	Level III	17-Jun-92
INDUSTRIAS BACHOCO	IBA	NYSE	1:6	Food	Level III	26-Sep-97
INTERNACIONAL DE CERAMICA	ICM	NYSE	1:5	Building Materials	Level III	15-Dec-94
TELEFONOS DE MEXICO S.A. DE C.V.- SERIES 'L'	TMX	NYSE	1:20	Fixed Line Comm.	Level III	13-May-91
TV AZTECA, S.A. DE C.V.	TZA	NYSE	1:16	Broadcasting	Level III	1-Aug-97
VITRO, S.A. DE C.V.	VTO	NYSE	1:3	Industrial Diversified	Level III	19-Nov-91

TABLE 2: MARKET STATISTICS

SYMBOL	Volume[1]	MC	Float[2]	Short Rate[2]	Mean (Q_t)	SD (Q_t)	Max/Min	AR(1)	LB(5)
AMX	1,531,594	22.13B	386.70M	3.155	0.1154	1.0538	8.27/-9.46	0.391	207.31
CX	617,121	9.87B	139.84M	2.586	-0.4298	0.9613	5.44/-6.26	0.490	844.66
KOF	179,258	3.83B	27.08M	1.909	0.3720	1.8516	12.79/-9.82	0.414	615.21
CDG	23,641	55.10M	2.30M	5	16.575	58.1485	483.44/-52.00	0.988	116118.20
DES	50,501	665.14M	34.66M	2.667	-10.55	6.6358	14.01/-37.29	0.917	8659.15
ICA	266,505	615.47M	71.20M	16.645	-2.6896	2.4973	13.66/-17.53	0.456	1427.63
FMX	237,435	4.78B	66.26M	2.851	-0.1025	0.9973	7.56/-17.41	0.194	81.35
GMK	8,323	743.26M	21.68M	7.25	0.6519	3.9613	14.19/-81.40	0.479	758.81
ASR	130,500	587.40M	10.80M	0.407	0.8898	6.8541	86.48/-12.32	0.810	1172.07
IMY	19,590	1.13B	10.02M	9.5	0.5551	2.5380	28.56/-17.34	0.633	1842.60
MSK	33,240	397.98M	4.42M	N/A	0.5484	2.4037	14.38/-29.99	0.501	1539.18
CEL	150,975	116.56M	4.72M	18.2	-0.3614	4.4567	22.51/-29.53	0.667	1291.53
RC	37,263	98.50M	8.68M	2.042	2.7286	9.3029	64.47/-24.51	0.898	8233.55
SIM	11,000	298.47M	16.10M	1.978	1.0113	11.17	77.66/-59.88	0.874	8139.64
TV	692,304	5.98B	105.89M	2.884	0.0915	1.1807	16.28/-11.14	0.267	291.30
TMM	62,341	150.38M	6.30M	16.968	-0.6590	15.3707	101.31/-68.87	0.963	12768.54
IBA	18,586	471.38M	8.17M	1.294	0.1688	2.7932	17.90/-12.13	0.702	2054.45
ICM	6,945	107.68M	5.54M	N/A	3.5991	13.2577	64.95/-49.16	0.955	9441.14
TMX	2,520,634	19.09B	392.98M	8.095	0.6146	0.971	16.53/-10.86	0.305	730.84
TZA	440,805	1.49B	72.68M	7.42	-0.2084	1.4993	10.64/-10.26	0.309	259.07
VTO	164,141	304.66M	24.70M	4.636	0.3206	2.2561	14.81/-17.16	0.473	1819.54

Notes:
1. MC: Market Capitalization; Volume: average daily volume since inception, Float: number of freely traded shares in the hands of the public. Float is calculated as Shares Outstanding minus Shares Owned by Insiders, 5% Owners, and Rule 144 Shares. Mean(Par_t) is the mean of $Q_t = 100*(B\ S_t\ P_t(L) / P_t(A)\ -1)$; SD($Q_t$) is the SD of Q_t; Max/Min represents the maximum and the minimum of Q_t; AR(1) is the AR(1) coefficient of Q_t; and LB(5) is the Ljung-Box statistics with 5 lags for Q_t.

2. As of May 18, 2004. N/A: Not available

TABLE 3: LM-Tests for Nonlinearity and LM-Tests for Model Selection

FIRM	Tests	Standard Tests					Heroskedasticity-Robust Tests				
		AR vs STAR		ESTAR vs LSTAR			AR vs STAR		ESTAR vs LSTAR		
	d	TP	EJP	TP	EJP		TP	EJP	TP	EJP	
		NLM3	NLM4	NLM2	LM^{LST}	LM^{EST}	NLM3	NLM4	NLM2	LM^{LST}	LM^{EST}
Panel A	1	0.000	0.000	0.000	0.000	0.000	0.387	0.390	0.042	0.016	0.002
TMX	**2**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.049**	**0.037**	**0.078**	**0.345**	**0.083**
	3	0.000	0.000	0.000	0.000	0.000	0.008	0.601	0.138	0.098	0.092
	4	0.000	0.000	0.000	0.127	0.000	0.316	0.271	0.192	0.821	0.162
	5	0.000	0.000	0.002	0.009	0.043	0.263	0.426	0.220	0.404	0.430
Panel B											
AMX	4	0.000	0.000	0.001	0.001	0.000	0.021	0.037	0.002	0.035	0.017
CX	2	0.000	0.029	0.000	0.002	0.000	0.200	0.569	0.169	0.101	0.113
KOF	1	0.000	0.000	0.013	0.000	0.020	0.069	0.059	0.049	0.073	0.037
CDG	1	0.000	0.019	0.000	0.002	0.000	0.020	0.599	0.069	0.091	0.063
DES	1	0.000	0.000	0.010	0.000	0.020	0.054	0.070	0.041	0.093	0.057
ICA	1	0.000	0.000	0.015	0.000	0.000	0.000	0.000	0.576	0.519	0.530
FMX	1	0.000	0.000	0.004	0.032	0.000	0.072	0.042	0.051	0.051	0.014
GMK	1	0.000	0.000	0.027	0.000	0.644	0.030	0.051	0.094	0.045	0.002
ASR	1	0.000	0.000	0.000	0.000	0.000	0.112	0.066	0.032	0.071	0.033
IMY	1	0.000	0.000	0.000	0.000	0.000	0.202	0.034	0.053	0.054	0.032
MSK	2	0.000	0.007	0.000	0.026	0.003	0.046	0.270	0.037	0.074	0.055
CEL	4	0.000	0.019	0.001	0.053	0.000	0.057	0.031	0.095	0.099	0.023
RC	1	0.000	0.012	0.001	0.080	0.020	0.072	0.065	0.068	0.097	0.053
SIM	1	0.000	0.000	0.120	0.007	0.067	0.002	0.048	0.029	0.034	0.051
TV	1	0.000	0.000	0.000	0.001	0.000	0.045	0.055	0.032	0.107	0.092
TMM	1	0.000	0.000	0.000	0.000	0.000	0.004	0.027	0.076	0.088	0.078
IBA	2	0.000	0.001	0.010	0.001	0.016	0.032	0.019	0.164	0.026	0.014
ICM	1	0.000	0.000	0.000	0.000	0.000	0.151	0.046	0.105	0.062	0.043
TMX	2	0.000	0.000	0.000	0.000	0.000	0.049	0.037	0.078	0.345	0.083
TZA	5	0.000	0.000	0.004	0.000	0.070	0.013	0.018	0.057	0.081	0.043
VTO	2	0.000	0.000	0.268	0.025	0.082	0.080	0.067	0.063	0.081	0.052

Notes: This Table presents the p-values of the Lagrange Multiplier (LM) tests for AR linearity against STAR nonlinearity, denoted AR vs. STAR and LM-tests for choosing between the ESTAR and the LSTAR model, denoted ESTAR vs. STAR of the daily price differential between ADRs and their underlying shares. The tests are performed following two tests: the Teräsvirta (1994) test (TP) with the corresponding statistics NLM3, and NLM2; and the Escribano and Jordá (1999) test (EJP) with corresponding statistics NLM4, LM^{LST}, and LM^{EST}. The NLM3 and NLM2 statistics are based on the auxiliary regression model, equation (A.1) and the NLM4, LM^{LST}, and LM^{EST} statistics are based on equation (A.2). For each test, two versions of tests are estimated, the standard test and the heteroskedasticity-consistent test.
The first panel shows p-values for all possible choices of d, d={1,…,5} only for the firm TMX. The second panel also reports the selected p-values and the delay parameter, d, for all the other firms. For each test, the rejection of the null hypothesis, the selection of the delay parameter d, and the resultant model are based on the smallest p-value.

TABLE 4: Nonlinear Estimation Results for ESTAR model of Price Spread

$$\textbf{ESTAR(P):}\quad \mathbf{q_t} = \boldsymbol{\mu} + \sum_{j=1}^{p}\psi_{1j}L^{j}(q_t - \mu) + \left[\sum_{j=1}^{p}\psi_{2j}L^{j}(q_t - \mu)\right][1 - \exp\{-\lambda(q_{t-d} - \mu)^2/\hat{\sigma}^2_{z_t}\}] + \boldsymbol{\varepsilon_t}$$

FIRM	p, d	μ	λ	Ψ_{11}	Ψ_{12}	Ψ_{21}	Ψ_{22}	S	LR(k)	NL_{Max} d={3..6}	LMNA AR(1-6)
AMX	2, 4	-	**2.745**	0.842	0.155	-0.837	-0.137	0.453	LR(4)	[0.498]	[0.336]
			(0.019)	(0.106)	(0.082)	(0.547)	(0.544)		[0.561]		
CX	2, 2	-	**2.864**	0.494	0.259	-0.470	-0.258	0.061	LR(3)	[0.502]	[0.452]
			(0.008)	(0.066)	(0.046)	(0.108)	(0.114)		[0.754]		
KOF	1, 1	0.045	**1.575**	0.643	-	- 0.612	-	0.036	LR(1)	[0.471]	[0.357]
		(0.001)	(0.025)	(0.049)		(0.077)			[0.224]		
CDG	1, 1	-	**1.981**	0.993	-	-0.996	-	0.041	LR(3)	[0.211]	[0.405]
			(0.528)	(0.009)		(0.048)			[0.582]		
DES	2, 1	0.163	**2.971**	0.921	0.164	-0.928	0.141	0.028	LR(3)	[0.404]	[0.471]
		(0.003)	(0.068)	(0.050)	(0.048)	(0.062)	(0.066)		[0.672]		
ICA	2, 1	-0.221	**0.992**	-0.765	-0.213	0.548	0.098	0.039	LR(3)	[0.397]	[0.545]
		(0.012)	(0.082)	(0.113)	(0.108)	(0.082)	(0.074)		[0.423]		
FMX	2, 1	-	**1.793**	0.865	0.147	-0.859	-0.161	0.027	LR(4)	[0.438]	[0.443]
			(0.014)	(0.011)	(0.075)	(0.070)	(0.094)		[0.522]		
GMK	1,1	-	**0.361**	0.839	-	-0.841	-	0.042	LR(2)	[0.399]	[0.562]
			(0.039)	(0.234)		(0.043)			[0.252]		
ASR	1, 1	-	**1.277**	0.806	-	-0.809	-	0.021	LR(2)	[0.305]	[0.668]
			(0.027)	(0.122)		(0.439)			[0.252]		
IMY	2, 2	-	**0.642**	0.526	0.164	-0.535	0.160	0.048	LR(3)	[0.574]	[0.218]
			(0.030)	(0.121)	(0.113)	(0.109)	(0.114)		[0.352]		
MSK	2, 2	0.025	**0.582**	0.897	0.175	-0.876	-0.133	0.030	LR(3)	[0.327]	[0.525]
		(0.003)	(0.053)	(0.111)	(0.077)	(0.094)	(0.083)		[0.571]		
CEL	2, 4	-	**0.496**	0.611	0.305	-0.609	-0.095	0.041	LR(3)	[0.318]	[0.280]
			(0.038)	(0.071)	(0.066)	(0.123)	(0.132)		[0.471]		
RC	1, 2	0.211	**0.835**	0.876	-	-0.950	-	0.038	LR(1)	[0.390]	[0.572]
		(0.012)	(0.104)	(0.031)		(0.043)			[0.197]		
SIM	2, 1	0.348	**0.514**	0.911	0.234	-1.09	-0.239	0.052	LR(3)	[0.795]	[0.489]
		(0.010)	(0.099)	(0.084)	(0.065)	(0.183)	(0.173)		[0.458]		

TABLE 4 : (Continued) Nonlinear Estimation Results for ESTAR model of Price Spread

FIRM	p, d	μ	λ	Ψ_{11}	Ψ_{12}	Ψ_{21}	Ψ_{22}	S	LR(k)	NL_{Max} d={3..6}	LMNA AR(1-6)
TV	2, 1	-	**2.289** (0.030)	0.823 (0.158)	0.081 (0.139)	-0.824 (0.101)	-0.078 (0.073)	0.032	LR(4) [0.285]	[0.321]	[0.254]
TMM	1, 1	-	**0.315** (0.737)	0.973 (0.019)	-	-0.973 (0.019)	-	0.042	LR(2) [0.628]	[0.244]	[0.145]
IBA	2, 2	-	**1.550** (0.021)	0.638 (0.038)	0.296 (0.031)	-0.641 (0.274)	-0.278 (0.276)	0.019	LR(4) [0.356]	[0.275]	[0.323]
ICM	1, 1	-0.053 (0.014)	**0.317** (0.094)	0.975 (0.010)	-	-0.846 (0.039)	-	0.035	LR(1) [0.334]	[0.399]	[0.379]
TMX	2, 2	0.026 (0.001)	**2.853** (0.018)	0.718 (0.065)	0.261 (0.057)	-0.709 (0.456)	-0.131 (0.173)	0.010	LR(3) [0.573]	[0.589]	[0.258]
TZA	2, 5	-	**1.387** (0.013)	0.965 (0.042)	0.023 (0.042)	-0.978 (0.149)	0.127 (0.135)	0.031	LR(3) [0.628]	[0.535]	[0.332]
VTO	2, 2	-0.037 (0.005)	**0.984** (0.093)	0.771 (0.092)	0.156 (0.058)	-0.725 (0.065)	-0.134 (0.048)	0.019	LR(4) [0.425]	[0.419]	[0.425]

Notes:

P and d denote the autoregressive order and the number of period for the delay parameter respectively. $\mathbf{\Psi_{11}}$, $\mathbf{\Psi_{12}}$, $\mathbf{\Psi_{21}}$ and $\mathbf{\Psi_{22}}$ represent the estimated autocorrelation parameters, $\boldsymbol{\lambda}$ the estimated speed of transition, **μ** the estimated mean, and S the residual standard errors of models.

Figures reported in the squared brackets are the (p-values). ARCH tests conducted on the residuals of the estimated models indicated the presence of heteroscedasticity. Therefore numbers in parentheses denote heteroscedastic-consistent standard errors of estimates computed using Woodridge (1991). LMNA AR(1-6) is a LM -test statistics for testing the null hypothesis of no serial correlation in the residuals of order 1, up to 6 developed as in Eitrheim and Teräsvirta (1996). NL_{Max} denotes the maximum LM- test statistic of no additive nonlinearity with the delay length in the range from 3 to 6; they are constructed as in Eitrheim and Teräsvirta (1996). LMNA and NL_{Max} allow the assessment of models adequacy. LR(k) denotes a likelihood ratio test statistic for k parameters restrictions implicit to the estimated equation against the unrestricted ESTAR model. For example, LR(4) tests the significance of the following four restrictions $\mu=0$, $\Psi_{11}+\Psi_{12}=1$, $\Psi_{21}=-\Psi_{11}$, and $\Psi_{22}=-\Psi_{12}$.

TABLE 5: **Speed of Convergence: Half-lives**

FIRM	Nonlinear Adjustment (ESTAR)[a]			Linear Adjustment (AR)[b]
	$1\hat{\sigma}_\varepsilon$	$3\hat{\sigma}_\varepsilon$	$5\hat{\sigma}_\varepsilon$	q_t (5)
AMX	0.643	0.588	0.507	0.850
CX	0.516	0.544	0.514	2.318
KOF	0.701	0.634	0.612	0.839
CDG	10.895	10.759	9.661	50.027
DES	2.356	2.267	1.084	12.313
ICA	12.908	12.772	11.674	15.685
FMX	0.542	0.497	0.494	0.505
GMK	1.079	0.968	0.555	0.732
ASR	0.945	0.892	0.712	2.287
IMY	0.986	0.866	0.793	2.057
MSK	1.042	1.045	0.947	1.691
CEL	2.094	2.195	2.183	2.601
RC	3.616	3.527	2.344	7.014
SIM	1.893	1.846	1.008	7.363
TV	0.694	0.664	0.666	0.704
TMM	12.575	12.439	11.341	32.550
IBA	1.995	1.764	1.103	2.344
ICM	7.116	7.027	5.844	7.014
TMX	0.551	0.458	0.475	1.040
TZA	0.606	0.603	0.603	0.792
VTO	1.164	0.976	0.832	1.799
Average	3.10	3.02	2.57	7.26

Notes: All figures are in (business) days. A half-life is defined as the number of periods it takes for shocks to pricing error to dissipate by a half. In a non-linear framework, it is such that the impulse response function is less than unity or $G_h(\delta, \omega_{t-1})<0.5$

a. Half-lives for shocks $\delta = i\hat{\sigma}_{\varepsilon\ (i=1,3,5)}$ where $\hat{\sigma}_\varepsilon$ denotes the residual standard deviation

b. Half-lives computed in a linear framework, using the Augmented Dickey-Fuller (ADF) representation, which regresses the first difference of the price spread $\mathbf{q_t}$ on a deterministic component, its lagged level, and *k* lagged first differences:

$$\mathbf{(1-L)q_t = d_t + \alpha\, q_{t-1} + \sum_{j=1}^{k} \phi_j(1-L)q_{t-j} + \varepsilon_t,}$$

where L denotes the lag operator, ε_t the error term, $\boldsymbol{\alpha}$, the persistence parameter, and $\mathbf{d_t}$ the deterministic component which can be a constant, $\boldsymbol{\mu_0}$, or a constant and a time trend, $\boldsymbol{\mu_0+\beta t}$, and *k* denotes the autoregressive lag length. The maximum lag length in the ADF specification is set equal to 5 business days. The lag truncation is selected using a general-to-specific methods.

<u>Table 6.A</u>: Ranks of Firms Market Characteristics

FIRM	Speed of transition	Price spread Nonlinear Half-life	Price spread Linear Half-life	Average Daily Volume	Market Capitalization	Float
AMX	4	5	6	2	1	2
CX	2	1	12	4	3	3
KOF	8	7	5	8	6	9
CDG	6	19	21	16	21	21
DES	1	16	18	13	10	8
ICA	12	21	19	6	11	6
FMX	7	2	1	7	5	7
GMK	19	11	3	20	9	11
ASR	11	8	11	11	12	13
IMY	15	9	10	17	8	14
MSK	16	10	8	15	14	20
CEL	18	15	14	10	18	19
RC	14	17	15	14	20	15
SIM	17	13	17	19	16	12
TV	5	6	2	3	4	4
TMM	21	20	20	12	17	17
IBA	9	14	13	18	13	16
ICM	20	18	16	21	19	18
TMX	3	3	7	1	2	1
TZA	10	4	4	5	7	5
VTO	13	12	9	9	15	10

<u>Table 6.B</u>: Nonparametric Tests of Association Between Firm Market Characteristics and Convergence to Parity: Spearman Rank Correlation Coefficient (r_s)

	Average Daily Volume	Price spread Nonlinear Half-life	Price spread Linear Half-life	Market Capitalization	Float
Speed of Transition	**0.627**	**0.513**	**0.223**	**0.633**	**0.651**
Average Daily Volume		**0.579**	**0.404**	**0.513**	**0.777**
Price spread Nonlinear Half-life			**0.810**	**0.826**	**0.655**
Price spread Linear Half-life				**0.702**	**0.505**
Market Capitalization					**0.852**

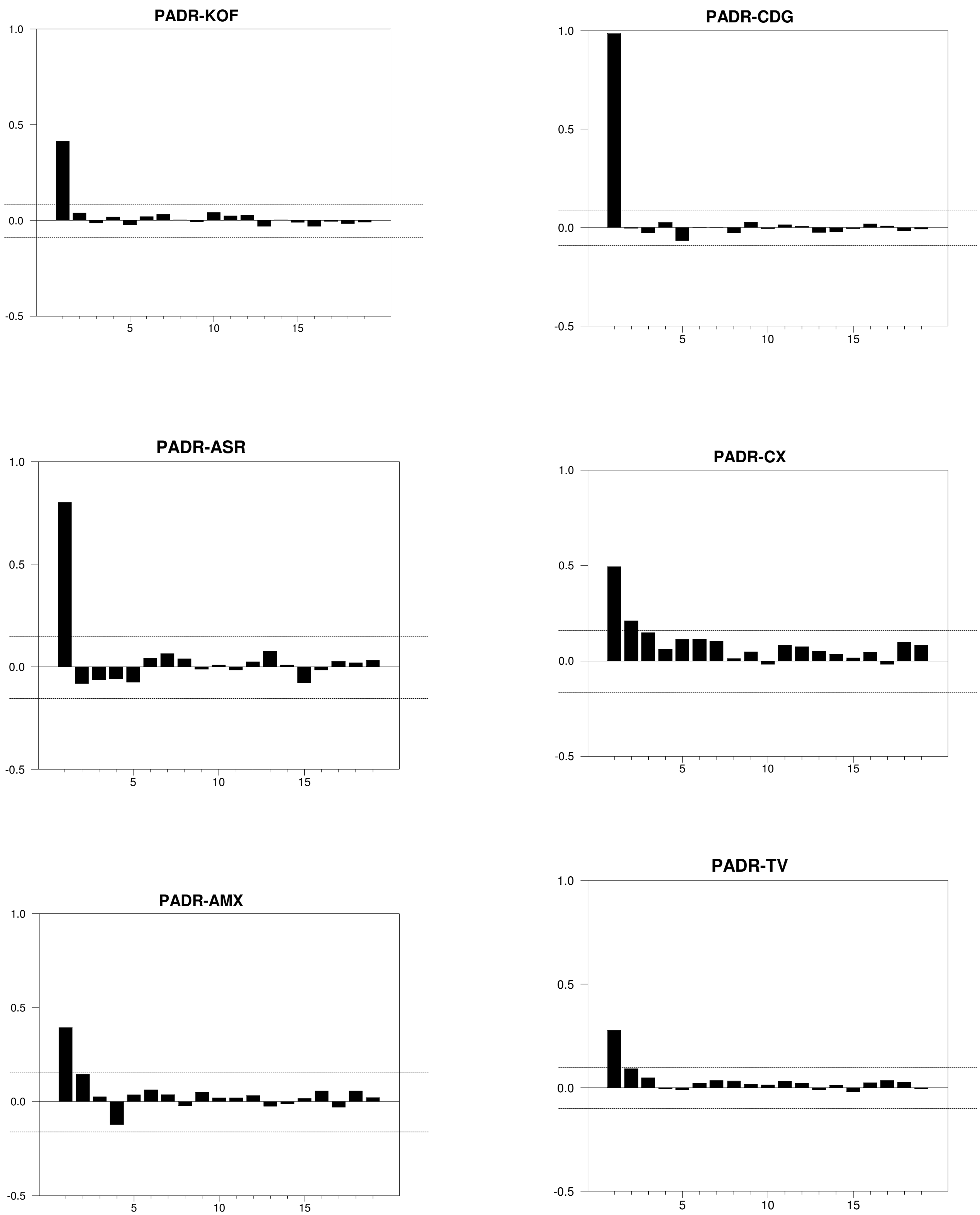
Notes:

The Spearman rank correlation coefficient is computed using the ranks as the paired measurements on the variables (x_i, x_j). The test statistic is therefore, assuming no ties in either the x or y observations, given by:

$$r_s = 1 - 6 \sum_{j=1}^{N} [R(x_{1,j}) - R(x_{2,j})]^2/[N(N^2 - 1)], \qquad | r_s | \leq 1$$

* denotes significance at the 5% level. The Spearman rank statistics indicate that volume, market capitalization, and float are positively and strongly correlated with the price spread half live and the speed of transition. This implies the higher the average daily volume, the faster an arbitrage can be executed. This observation remains true for market capitalization and float. Critical values of Spearman's Rank correlation coefficient for n=21 are: 0.368 (5%); 0.438(2.5%); and 0.521(1%).

Figure 1: Partial Autocorrelation Function for q_t for Selected Firms

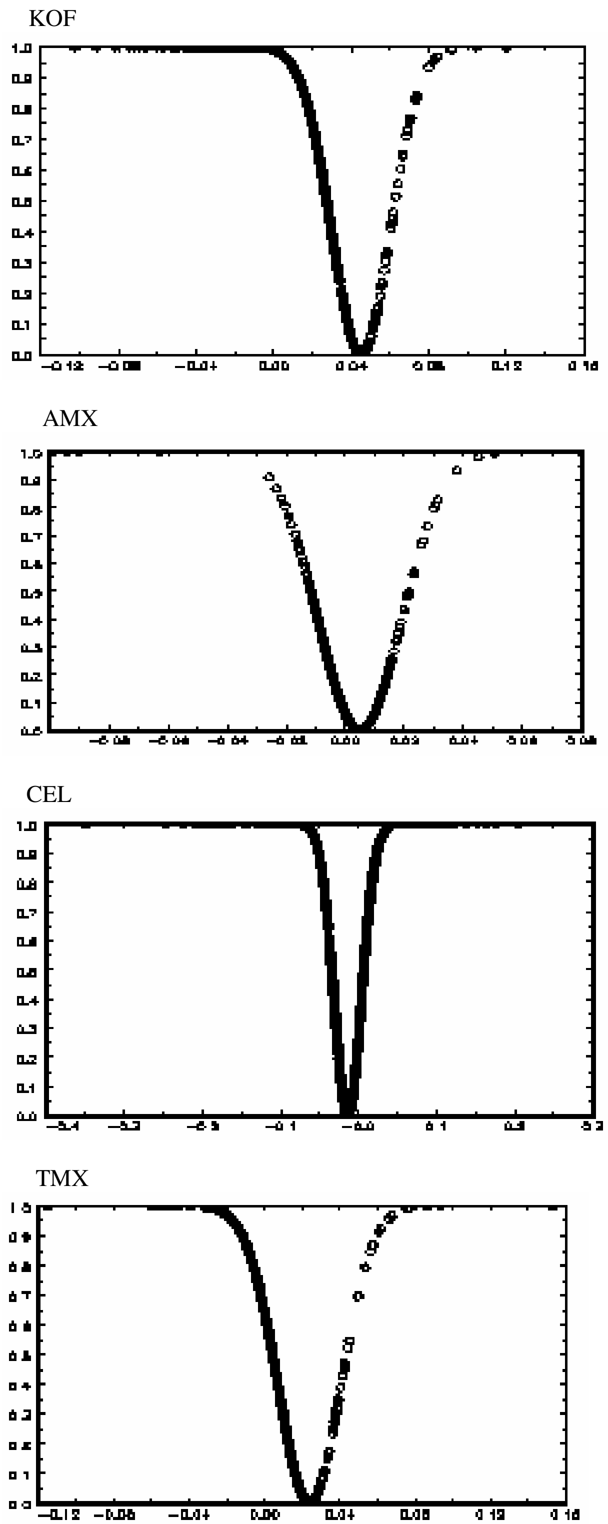


Notes: The band on the PACF represents the 95% confidence interval.

Figure 2: Estimated Transition Function for Selected Firms

Panel A: Transition Function vs. Transition Variable

$\Phi(Z_{t-d};\lambda,\mu)$ v.s. z_{t-d}



Panel B: Transition Function vs. Time

$\Phi(Z_{t-d};\lambda,\mu)$ v.s. t

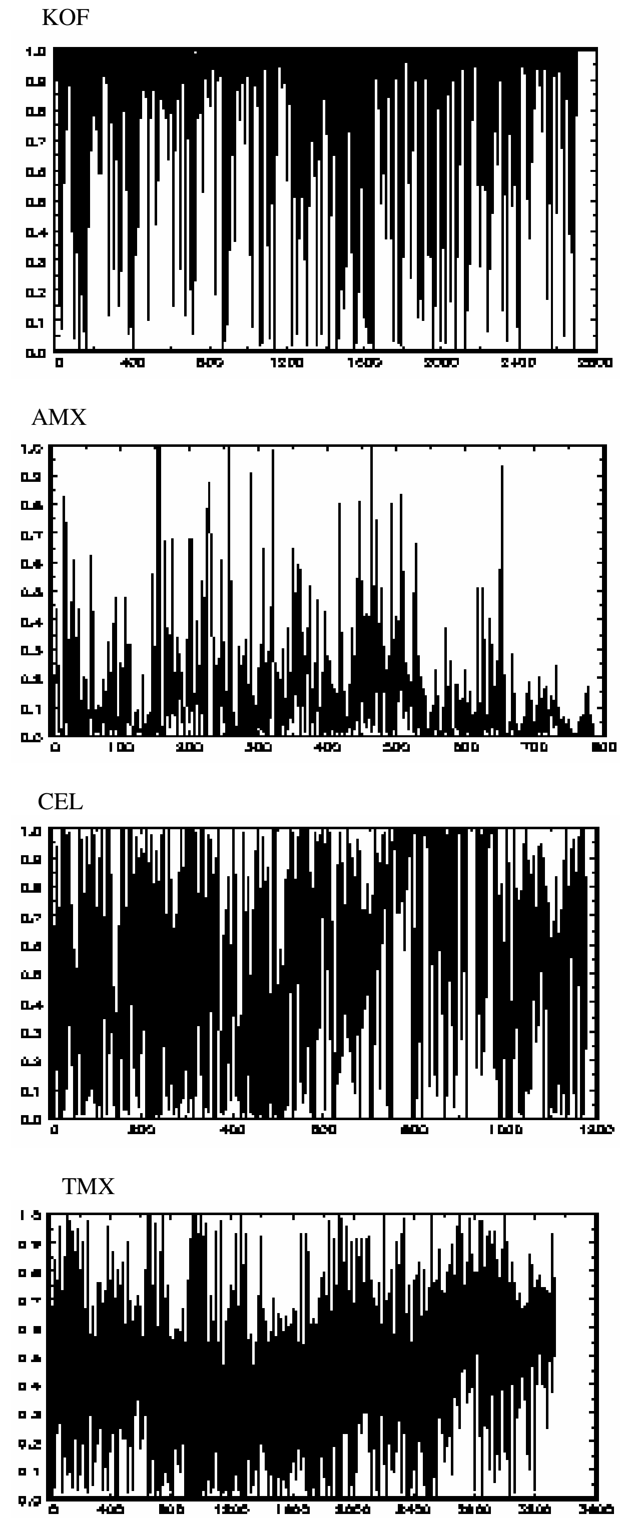
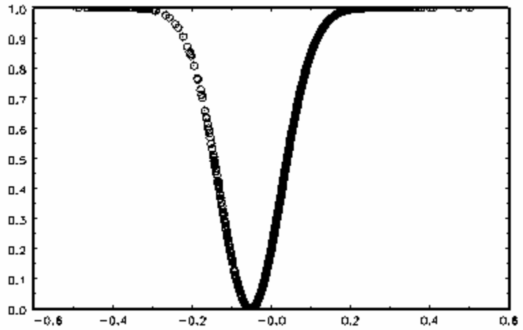


Figure 2: Estimated Transition Function for Selected Firms (continued)

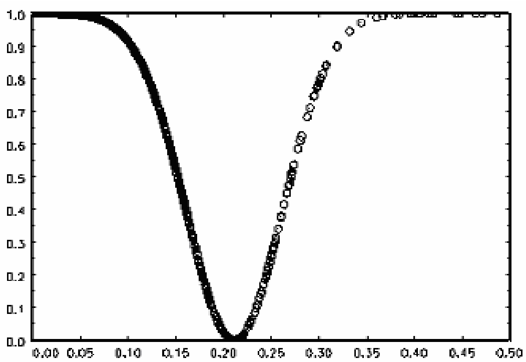
Panel A: Transition Function vs. Transition Variable

$\Phi(Z_{t-d};\lambda,\mu)$ v.s. z_{t-d}

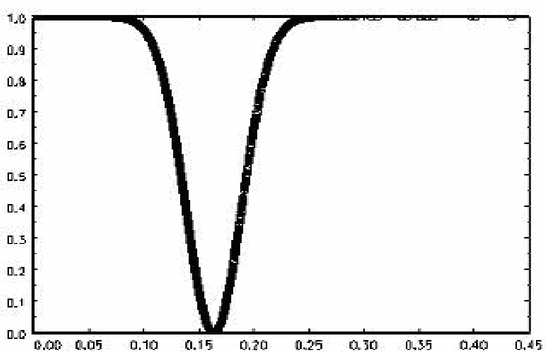
ICM



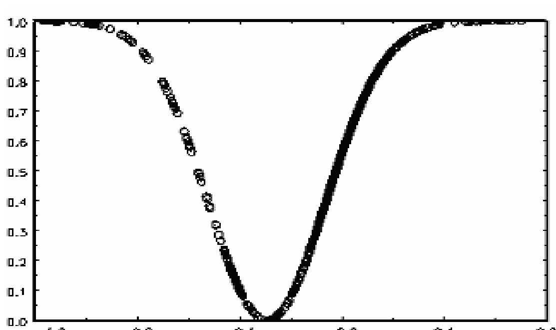
RC



DES



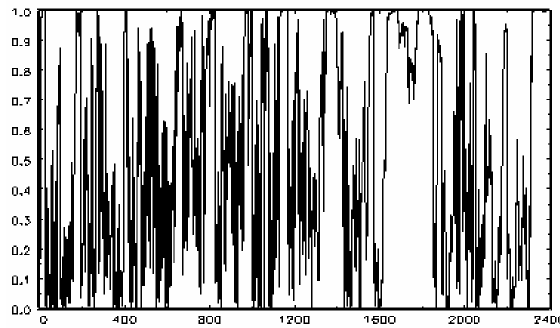
TMM



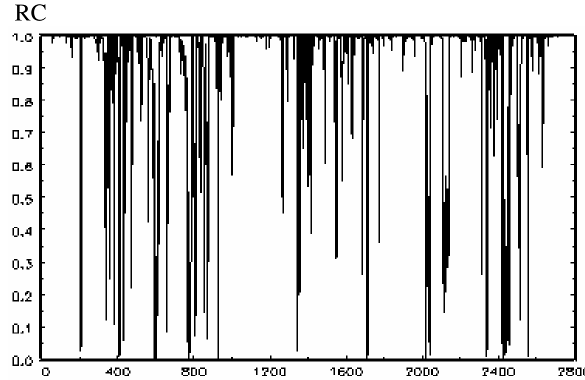
Panel B: Transition Function vs. Time

$\Phi(Z_{t-d};\lambda,\mu)$ v.s. t

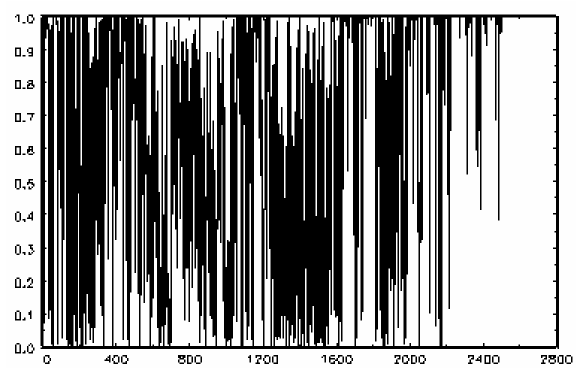
ICM



RC



DES



TMM