Tender Offers in South America: Do They Convey Good News to the Market?

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Abstract

Different studies in developed capital markets have found positive abnormal returns of at least 15% during the announcement date of a tender offer. Although there are almost no studies for South American stock markets, one study reported positive abnormal returns, ranging from 25% to 50%, related to the announcement of the first tender offer. This study argues that estimated positive abnormal returns in emerging markets are high because studies have assumed a completely segmented capital market by applying the market model with a local stock market index. By allowing for partial integration among five South American emerging markets, one shows that there are in fact positive abnormal returns previously, during, and after the announcement date of the first tender offer. However, the positive abnormal return associated to the announcement date is around 8%. A slightly higher abnormal return is obtained using a market model that accounts for partial integration and downside risk. These results prompt towards a lower positive abnormal return in the sample of South American firms studied.

Key words: tender offer, abnormal return, emerging market.
JEL Code: C12, C32, G34.

Introduction

There have been several studies in the field of tender offers and on the necessary premia to get corporate control in the process of takeover in developed capital markets, but almost none for South American stock markets. International evidence, mainly in the United States, shows that there are high positive abnormal returns for the target company at the moment of announcing the tender offer.

The objective of this study is to show that positive abnormal returns related to the first tender offer are in fact lower than previous estimates when capital markets are allowed to be partially integrated instead of completely segmented. Recently, Stulz (1999), and Bekaert and Harvey (2003) have shown that after financial liberalization in emerging markets, a expected returns must fall because their volatility must be higher in comparison to the world volatility than their correlations with the world market returns. This is the case even when emerging markets are more sensitive to world events due to their financial liberalizations.[1] To the extent that local and world events play a meaningful role in explaining stock returns in emerging markets, there will be less variation to explain and therefore abnormal returns must be lower than otherwise.

This research shows that accounting for partial integration among five South American stock markets yields positive abnormal returns, which are lower than those estimated by previous studies. In order to prove it, 17 tender offers, that have been accomplished during the period 1998–2002, are used across five South American stock markets (Argentina, Brazil, Chile, Peru and Venezuela). In this sense, we raised several questions: Do target South American firms offer positive abnormal returns around the announcement date of their first tender offer in a situation of partial integration? Does it exist evidence of information linkage during the days previous to the announcement date of the first tender offer? Is there evidence of stock market overreaction?

To answer thern, a hybrid multifactor Capital Asset Pricing Model (CAMP) is used as a market model; in fact, is used this is just one way to represent a situation of partial integration. As pointed by Bodnar et al. (2003), it is very difficult to represent a situation of partial integration due to the fact that each investor has access to an incomplete but well-defined list of stocks. In order to specify this situation, we require information about all individuals and their available securities. Hence, it may be possible that a situation of partial integration does not correspond

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[1] In fact, the emerging market covariance with the world return may increase due to the financial liberalization.

to the hybrid multifactor CAPM. However, since the hybrid multifactor CAPM is a strange mix of the full-integration and the full-segmentation CAPM, it can be considered as a first approximation to a situation of partial integration.

This paper has been divided into six sections. The next section discusses the existing empirical evidence concerning tender offers, while the third section reviews the main aspects related to event studies. The sample criteria and data description appear in the fourth section, while the methodology and results are showed in the fifth section. Finally, we present our conclusions.

1. Tender Offers: Empirical Evidence

A takeover is an agreement between two parties, the controlling shareholders of a target company and the controlling shareholders of the bidder company, where the later group wishes to acquire the target company. The empirical evidence concerning tender offers is vast, so this section summarizes the most relevant studies for the purposes of this research.

Dodd and Ruback conducted one of the earliest studies concerning tender offers in (1977), they studied 172 companies traded at the New York Stock Exchange (NYSE) covering the period from 1958 to 1976. The objective of their study was to analyze the premium obtained by target companies on the announcement date of a tender offer and whether this premium was different for successful and unsuccessful bids. Using the market model, these authors found that abnormal returns of target companies acquired via successful bids was about 21%, while it was 19% for the case of unsuccessful bids. Later on, Jensen and Ruback (1983) conducted several studies between 1977-1983 and concluded that in their sample takeovers have offered positive abnormal returns ranging between 16% and 30%.

Through the years, several authors have found similar results for the NYSE and the NASDAQ. In this sense, Bredley et al. (1983) reported a premium ranging between 23% and 60%; and Jarrel et al. (1988) studied 663 cases of successful tender offers between 1962-1985 and came to the conclusion that positive abnormal returns for target companies averaged 30%. Furthermore, Asquith (1988) found a positive abnormal return of 19% on NASDAQ target companies 10 days prior to a tender offer announcement, result that prompts to information linkage.

Zingales (2000) studied the magnitude of the average premium for voting shares in countries where the menitoned information is available. Such average premium varies enormously from country to country. In most of them, it fluctuates

between 10% and 25%, where Israel (45%) and Italy (82%) as the main exceptions. This variation can be explained by the characteristics of each country, with a probable effect on the ability to obtain private gains from company control. Zingales concludes that as both local legislation and supervision improve, the premia on controlling stock will tend to be lower. Another interesting result was obtained by Moloney (2002) who found that, on average, the bidder company rewards the target company between 15% and 50% over the market price of the target company prior to the announcement of the tender offer. He concluded that there is a high positive abnormal return in the case of hostile bids and that there is a low positive abnormal return when ownership is highly concentrated and absorbed.

Although there are almost no studies for South American emerging markets, an interesting piece of evidence was offered by Fuenzalida and Nash (2003) whom studied 14 Chilean companies during the years 1995 and 2002. They concluded that there is evidence of positive abnormal returns (about 26%) on the announcement date of a tender offer, and these returns are lower for public companies operating under the Law of Tender Offers.

2. Issues in Event Studies

While conducting event studies, there are several issues that must be taken into account. In this need into section, the main stages of the procedure are revised. Five issues are discussed: event definition, selection criteria, estimation of abnormal returns, estimation of model parameters, and tests for detecting abnormal returns. The following subsections will discuss each one in turn.

2.1 Event Definition

The best results from an event study are obtained when the exact date of the event is identified. In order to do this, first it is crucial to identify the event subject: e.g. the announcement date of a merger, an acquisition, an earnings announcement, a change in the debt rating, the adoption of an ISO standard, etc. Then, the estimation and event windows must be determined (see Figure 1).

Figure 1
Event Study Windows[2]
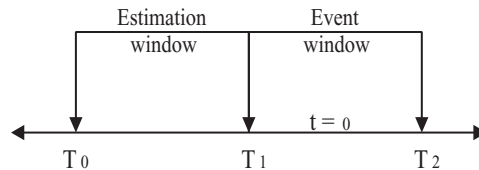
Using the same notation as Campbell et al. (1997), t=0 is defined as the event date in wich the announcement occurs; the interval [T1+1, T2] as the event window with length L2=T2-T1-1; and the interval [T0+1, T1] as the estimation window with length L1=T1-T0-1. When the study is being conducted with daily data, the estimation window usually is between 100 and 300 trading days (Peterson, 1989).

The length of the event window usually depends on the ability to establish precisely the announcement date. When it is established with precision, the event window will be short and the tests for identifyng abnormal returns will be more powerful. Nevertheless, the length of the event window normally goes from 21 to 121 days (Peterson 1989). Note that the event window includes the event announcement day, which occurs at t=0.

2.2 Selection Criteria

Certainly thisis a very important step since it is easy to introduce a selection bias in the definition of the firms sample that will be studied. In emerging markets the main tradeoff that must be made is either having quantitatively more firms in the sample but with several firms subject to thin trading; or having less number of firms, but actively traded. In the first case, it is necesary to use a procedure that tests for abnormal returns in the presence of thin trading; while in the second, any selection bias in the sample must be avoided.

This tradeoff is due to the low number of actively traded or liquid stocks in emerging markets. For example, the percentage of actively traded stocks as a fraction of the total number of traded stocks per year, was between 5% and 19% at the Lima Stock Exchange (LSE) during the period 1991–2002 (Mongrut, 2004).

Thin trading or non-synchronous trading implies that whenever a market shock occurs, it will not be incorporated immediately into the price of a thin traded

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[2] All Figures and Tables are own elaboration unless otherwise stated.

stock because it is not actually being traded. If the effect of thin trading is not considered, there will be a serious bias in the moments and co-moments of asset returns (for example, the beta parameters of thin traded stocks will be lower than the ones of actively traded stocks). The reason for this is that time series of stock prices are taken to be recorded at time intervals of one length when in fact they are recorded at other irregular time intervals (Campbell *et al.*, 1997).

Different ways to deal with the problem of thin trading have been suggested by Scholes and Williams (1977), Dimson (1979), and Cohen et al. (1983) in the context of market risk estimation. Each one of them tried to obtain an estimation of the market risk parameter (beta) in the presence of thin trading. However, as reported by Brown and Warner (1985), there is little to gain by using the procedures of Scholes and Williams (1977), and Dimson (1979) when testing abnormal returns.

What happens if one only includes few firms actively traded in the sample? A small number of firms will not represent a problem because parametric tests statistics used to detect abnormal returns converge to their asymptotic values rather quickly (Brown and Warner 1985). This implies that even in the presence of abnormal returns that do not obey a normal distribution, parametric tests invoking the Central Limit Theorem can still be used. The real problem is a plausible selection bias. In our study, there could be observed and unobserved common characteristics among these few firms that make them more prone to become a target for a tender offer. In this sense, inferences cannot be drawned for the total population of tender offers. This issue will be addressed again in the fifth section.

2.3 Estimation of Abnormal Returns

There are mainly three models to estimate abnormal returns: the constant-mean return model, the market model, and the market adjusted model.[3] Nevertheless, in this research only the market model is used. In the following sections the market model will be discussed in tow alternative scenarios: full–segmentation of capital markets and partial integration.

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[3] Brown and Weinstein (1985) have concluded that there is little value to gain in using a multifactor model (such as the Arbitrage Pricing Theory-APT) versus the market model. Furthermore, Dyckman et al. (1984) have concluded that the market model is more suitable for detecting abnormal performance.

2.3.1 The market Model with Full-Segmentation

The market model with full-segmentation states that:

$$AR_{i,t} = R_{i,t} - (\alpha_i - b_i R_{m,t}^L)$$ (1)

Where:

$AR_{i,t}$:   Abnormal return of stock i in period t.

$R_{i,t}$:   Realized return of stock i in period t.

$R_{m,t}^L$:   Return of a local market index in period t.

The market model adjusts for the stock return for the local systematic risk in estimating the abnormal return. In this way, the variance of the abnormal return will be reduced because the portion of the return that is related to the local market index is removed. Popular choices for the market index are the local equally weighted market index and the local value weighted market index. However, the former index is more likely to detect abnormal returns because it has been shown that is more correlated with market returns (Peterson, 1989).

Usually, the model parameters (alpha and beta) are estimated using Ordinary Least Squares (OLS) during the estimation window. The OLS estimation of Equation 1 relies on two crucial assumptions: the variance of the abnormal return is constant through time and there is no time series correlation among the abnormal returns. Hence, the model implies absence of heteroskedasticity and serial correlation. Unfortunately, these assumptions are usually not met. In particular, thin trading could generate times series dependence or serial correlation.

If there is heteroskedasticity and serial correlation in abnormal returns it is better to use a different method to estimate the model parameters such as the Generalized Autoregressive Conditionally Heteroskedastic Model (GARCH). The GARCH (1,1) is expressed in the following way:

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i^L\ R_{m,t}^L)$$
$$AR_{i,t} = \rho_i AR_{i,t\text{-}1} + \varepsilon_{i,t}$$ (2)
$$h_{i,t} = \omega_{i,0} + \omega_{i,1}\, \varepsilon_{i,t-1}^2 + \omega_{i,2}\, h_{i,t\text{-}1}$$

Where:

$e_{i,t} \sim N(0, h_{i,t})$

Furthermore, event clustering within the same time period could generate another problem: cross-correlation among abnormal returns of different stocks. Although, Brown and Warner (1985) have noted that, unless the potential bias is substantial, it is better to assume cross-sectional independence, it is wise to avoid event clustering otherwise the statistical power of the tests will diminish.

Another problem is a variance increase due to the event announcement. This also generates the problem of heteroskedasticity. If the variance of the estimation window is used instead of the variance of the event window, the tests statistics will yield too many rejections of the null hypothesis (cumulative average of the abnormal return is to zero). A way to deal with this problem is by using the standardized cross-sectional test proposed by Boehmer et al. (1991).

The OLS estimation of the model parameters also relies on the assumption that abnormal returns are normally distributed. There is considerable evidence that daily stock returns (raw returns), and their respective abnormal returns, are right skewed and leptokurtic (fat tails) (Fama 1976). In emerging markets, stock returns are considerable more skewed and leptokurtic than in developed markets (Bekaert et al. 1998). Although the parametric tests statistics converge rather quickly to a normal distribution, it is advisable to estimate the model parameters using a procedure that allows for the non-normality in the cross-section of abnormal returns, such as the Theil procedure proposed by Dombrow et al. (2000) or to use a non-parametric test to test for abnormal returns. In particular, one may use two nonparametric tests: the sign test analyzed by Cowan (1992) or the rank test proposed by Corrado (1989).

2.3.2 The Market Model with Partial Integration

Emerging markets are not completely segmented, but rather partially integrated (Bodnar et al. 2003). In such situation, a better way to specify abnormal returns is te use a hybrid version of the market model where local and world events play a role in explaining stock returns:

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i^L \ R_{m,t}^L + \hat{\beta}_i^W \ R_{m,t}^W) \tag{3}$$

Where:

$R_{m,t}^W :$ Return of a global market index in period t.

This model can be estimated using both OLS or GARCH, but given the high volatility of emerging markets it is better to use the later procedure to estimate the model parameters within the estimation window.

As previously stated, stock returns in emerging markets are non-normal because they are usually right skewed. In other words, investors in these markets face substantial downside risk (Estrada 2000). In this sense, Estrada (2002) proposed a modification of the traditional CAPM in order to allow downside risk, the result was the D-CAPM. This model states that what matters to expected returns in emerging markets is the downside systematic risk or downside beta as opposed to the total systematic risk or beta from the traditional CAPM.

The ex-post version of a hybrid D-CAPM can be used to estimate abnormal returns. This version is expressed as follows:

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i^{DL} Min[(R_{m,t}^L - \overline{R}_m^L),0] + \beta_i^{DW} Min[(R_{m,t}^W - \overline{R}_m^W),0]) \qquad (4)$$

This version considers partial integration and downside risk simultaneously. Furthermore, given the non-normality of emerging market stock returns, the parameters of models 3 and 4 can be estimated using the GARCH procedure.

2.4 Tests for Abnormal Returns

Once abnormal returns have been estimated for each stock, using one or more models, it is in order to test whether abnormal returns are statistically significant or not. This task can be performed for each day or for a time interval during the event window. The test for each day aims to test whether individual cumulative abnormal returns are statistically significant, while the test for a time interval to determine the statistical significance of cumulative average abnormal returns during a selected time interval for a group of stocks.

Two main situations can arise: only one event occurs per stock or each stock is subject to the occurrence of many events within the selected time interval. In both cases, parametric and nonparametric tests statistics may be used. The choice of one or more test statistics depends on the situation faced by the researcher. In emerging markets the situation usually is far from ideal, so the best way to proceed is by using a combination of parametric and nonparametric tests.

Parametric tests use standardized abnormal returns to align event period abnormal returns' volatility with its estimation period volatility, and to prevent

stocks with large volatility to dominate test statistics (Boehmer et al. 1991). The standardized abnormal return is given as follows:

$$SAR_{i,t} = \frac{AR_{i,t}}{S_{i,t}} \tag{5}$$

Where:
$SAR_{i,t}$: Standarized abnormal return for stock i within the event window.
$S_{i,t}$:   Standard error.

Cumulate abnormal return for each stock within the time interval $[t_1, t_2]$ is given as follows:

$$CAR_i\,(t_1,\,t_2) = \sum_{i=1}^{N} SAR_{i,t} \tag{6}$$

The standard error involves information both from the estimation window and from the event window because it must include the standard error of the estimate (from the estimation window) and the standard error of the forecast (from the event window).

Parametric tests can be defined to test for abnormal returns per each stock at any given date, but this research is focused in detecting aggregate abnormal performance for a given period or time interval. In such way, parametric and nonparametric test must be defined accordingly.

In order to aggregate abnormal returns across several stocks and events for a selected time interval $[t_1,\ t_2]$ (within the event window), the first step is to aggregate the individual abnormal returns considering N events. The average abnormal return for period "t" is as follows:

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \tag{7}$$

With: $Var(AAR_t) = \frac{1}{N^2} \sum_{i=1}^{N} S_{i,t}^2$.

The next step is to aggregate the average abnormal returns through the selected time interval. The result is as follows:

$$CAAR\ (t_1, t_2) = \sum_{i=1}^{N} AAR_t \qquad (8)$$

With: $Var\ (CAAR\ (t_1, t_2)) = \sum_{t=t_1}^{t_2} Var\ (AAR_t).$

$CAAR\ (t_1, t_2) \sim N\ (0,\ Var\ (CAAR\ (t_1, t_2))).$

The variance of CAAR assumes that different event windows do not overlap to each other (i.e. no event clustering), so covariance terms may be avoided. Then, in order to test the null hypothesis the following test statistic (MacKinlay 1997 and Campbell et al. 1997) is used:

$$J_1 = \frac{CAAR(t_1, t_2)}{[Var(CAAR(t_1, t_2)]^{1/2}} = \frac{CAAR(t_1, t_2)}{\left[\dfrac{1}{N^2} \sum_{t=t_1}^{t_2} \sum_{i=1}^{N} S_{i,\varepsilon}^2\right]^{1/2}} \qquad (9)$$

Where:
$J_1 \sim N\ (0,1)$

Whenever cumulative abnormal returns vary across securities, it is suitable to give equal weight to the realized cumulative abnormal return of each security. This is what J_1 does.

Another possibility is to consider constant abnormal returns across securities. In this case it is more appropriate to give more weight to the securities with the lower abnormal return variance so that the power of the test will improve. In order to construct a test consistent with this possibility, a test statistic for each security using the standardized cumulative abnormal return within the selected time interval [t_1, t2] (Patell, 1976) must be constructed:

$$SCAR_i\ (t_1, t_2) = \frac{CAR_i(t_1, t_2)}{\hat{\sigma}_i(t_1, t_2)} \qquad (10)$$

$$\text{Where: SCAR}_i \ (t_1, t_2) \sim T\left(0, \frac{L_1 - 2}{L_1 - 4}\right)$$

The standardized cumulative abnormal return has a Student-T distribution with a null expectation. As long as the length of the estimation window increases (L1 > 30), the distribution for this test converges to the standard normal distribution (Cowan and Sergeant 1996). Now, by aggregating expression 10 through the number of events within the selected time interval (Campbell et al. 1997):

$$\text{SCAAR} \ (t_1, t_2) = \frac{1}{N} \sum_{i=1}^{N} \text{SCAR}_i \ (t_1, t_2)$$

One obtains the second parametric test statistic:

$$J_2 = \frac{\overline{SCAAR(t_1, t_2)}}{\left[\left(\frac{1}{N}\right)\frac{L_1 - 2}{L_1 - 4}\right]^{\frac{1}{2}}} \tag{11}$$

Where: $J_2 \sim N(0,1)$. SCAAR (t_1, t_2):
Average standardized cumulative abnormal return for
the event window $[t_1, t_2]$.

Brown and Warner (1985) reported that the Patell's test (Equation 10) is well specified under a variety of conditions. Furthermore, there is little to gain by using a more complicated test unless there is a serious problem, suchas an increase in the variance of abnormal returns (induced by the event) or unusually high cross-correlation. If the variance of abnormal returns increases on the event date the Patell's test rejects the null hypothesis more often than the nominal significant level (Cowan and Sergeant 1996). In other words, increases of the event-related variance causes these tests to report a price reaction more often than expected (Cowan, 1992). In order to avoid this problem, the Boehmer et al. (1991) test, better known as the BMP test, may be used:

$$J_3 = \frac{\sum_{i=1}^{N} SCAR_i(t_1,t_2)}{[Var(SCAR(t_1,t_2))]^{\frac{1}{2}}} \qquad (12)$$

Where:

$$Var\ (SCAR\ (t_1,\ t_2)) = \left[\frac{N}{N-1} \sum_{i=1}^{N} \left(SCAR_i(t_1,t_2) - \frac{1}{N} \sum_{i=1}^{N} SCAR_i(t_1,t_2) \right)^2 \right].$$

Due to the fact that the BMP test works with data from the event window, it can consider any event-induced variance and it is not affected by the problem of thin trading. Furthermore, the test is essentially unaffected by the presence of event-date clustering (Boehmer et al. 1991).

Concerning the problem of non-normality, it can be tackled by using a nonparametric test, which does not rely on this assumption. Hence, there are two choices: either the generalized sign test or the rank test from Corrado (1989). The general rank test is more powerful than the generalized sign test in detecting abnormal returns, however in the presence of event induced variance different authors favor the generalized sign test. Besides, given that in the presence of non-normality both test are well specified and equally powerful. So this research favors the generalized sign test over the rank test.

The generalized sign test aims to determine whether the number of securities with positive cumulative abnormal returns in the event window exceeds the expected number in the absence of abnormal security performance (Cowan 1992). The expected number of positive abnormal returns along 214-day estimation period is given by:

$$\hat{p} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{214} \sum_{t=1}^{214} D_{i,t}$$

In the above expression, the dummy variable D takes the value of one whenever there is a positive abnormal return for security i on day t, otherwise is zero. Let ω be defined as the number of securities in the event window with a

positive cumulative abnormal return, so the generalized sign test statistic (S) can be written as follows:

$$J_4 = \frac{\omega - N\hat{p}}{[N\hat{p}(1-\hat{p})]^{\frac{1}{2}}} \tag{13}$$

Where: $J_4 \sim N(0, 1)$.

These four tests (three parametric and one nonparametric) will be used in the empirical part of this research.

3. Sample criteria and data description

Table 1 shows the total number of acquisitions in six South American capital markets. Only a small fraction of the total number of acquisitions fulfilled our sample criteria. The criteria to select a particular acquisition were based upon the following five requirements: the type of acquisition must be a tender offer; only target firms that have been subject to a first tender offer during the period 01/01/1998 to 12/31/2003 were selected; each firm in the sample must have a market presence of at least 60% during the estimation period and non-missing observations for the event period; there must be no other news besides the announcement of the tender offer during the analyzed period; and securities with overlapping event periods are excluded from the analysis unless they belong to different industries.

Table 1
Total Number of Acquisitions in South American Stock Markets[4]

Country	1998	1999	2000	2001	2002	2003
Argentina	61	63	79	26	8	21
Colombia	17	22	13	3	6	8
Brazil	94	96	137	77	40	69
Chile	15	43	47	24	10	13
Peru	7	20	17	7	6	15
Venezuela	6	14	17	11	8	4

Source: Bloomberg.

[4] The total number of acquisitions is based on the effective date of the acquisition instead of the announcement date of the acquisition.

The analysis period was chosed because none acquisition fulfilled our sample criteria during the three previous years: 1995-1997. The requirement of a market presence of at least 60% during the estimation period was meant to include as much firms as possible. However, as Table 2 shows only one firm had such low market presence, the remaining firms had more than 80% presence.

Table 2
Description of the Sample

Country	Target	% Presence	% Acquired	Announcement Date
Chile	Santa Isabel	99.6	14.0	15/01/1998
Chile	Banco Bhif	97.7	8.0	10/08/1998
Chile	Enersis	99.8	21.7	25/01/1999
Chile	Campos Chilenos	90.3	51.0	27/01/1999
Chile	Gener	100.0	95.7	03/11/2000
Chile	Laboratorio Chile	98.8	100.0	22/05/2001
Peru	Telefonica del Peru SAA	100.0	60.6%	13/01/2000
Peru	Banco Continental Peru	85.6	9.8	27/11/2002
Peru	Cía. Minera Atacocha SA	61.0	41.3	29/05/2001
Peru	Luz del Sur S.A	99.6	25.0	05/08/1999
Venezuela	Cía. Anónima Nacional Teléfonos de	100.0	43.2	29/08/2001
Venezuela	Venezuela - CANTV	99.6	73.0	02/05/2000
Argentina	Electricidad de Caracas	82.0	9.3	04/09/2000
Argentina	Telefónica Holding de Argentina, SA	100.0	15.0	06/01/1999
Argentina	YPF, SA	96.0	25.5	10/02/2000
Brazil	Banco Rio de la Plata SA	97.0	37.0	06/07/2000
Brazil	Empresa Bandeirante de Energía, SA Teleste Celular	86.0	60.1	16/06/1999

Source: Bloomberg and Economatica..

The indicator of presence is defined as follows:

$$P = \frac{q}{d} * 100$$

Where: q: Number of days in which there were at least 1 trade of the stock within the selected period.
d: Total number of days within the selected period.

Missing quotes were treated as suggested by Brown and Warner (1985): the missing quote and the succeeding period quote were removed from the analysis. This method attains the greatest sample size without affecting the identification of abnormal performance (Peterson 1989). The remaining two criteria were established to avoid any confounding effects and any cross-correlation due to event clustering, respectively.

Applying the selection criteria yields only 17 companies, which are reported in Table 2. Two observations are in order: there was no firm in Colombia able to fulfill the sample criteria, and there was no firm able to fulfill the sample requirements in 2003. Therefore, our results only apply for the period 1998-2002.

Given the small sample size a cause of concern is the possibility for a selection bias. In particular, one may wonder if there are observed and unobserved common characteristics among these few firms that make them more prone to become a target for a tender offer. However, it seems to be no selection bias due to observable variables. Indeed, target firms are based in different countries, the percentage acquired varies widely, bidder firms come from different countries (not reported), and target firms belong to different industries (see Figure 2).

Figure2
Target Firms by Sector
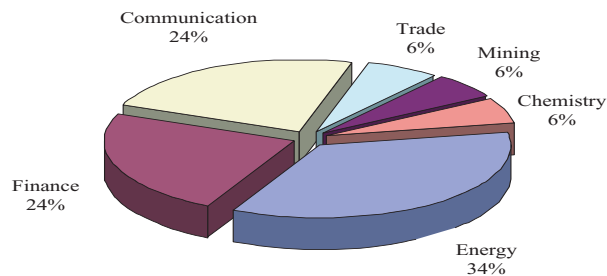
4. Methodology and Results

This section briefly explains the different steps used in this research to determine the daily abnormal performance of stock returns. The event under study is the announcement of a tender offer from the bidder firm to the target firm. In this sense, what matters is the announcement date of the tender offer instead of the effective date when the acquisition was made.

Around the announcement date reported in Table 2, it was defined an estimation period of 214 days and an event period of 30 days (20 days were defined prior to the announcement date and 10 days after). Hence, there are 245 days per stock, including the announcement date.

The market model was used to estimate daily abnormal returns per stock.[5] However, due to the fact that we are working with target firms from different countries, it's necesary to control for differences in the level of market integration across the five capital markets considered. Hence, it has been decided to use a hybrid version of the market model with and without downside risk. In other words, equations 3 and 4 were used to estimate daily abnormal returns. The hybrid market model does not include currency risk, so implicitly it's assumed that the influence of this risk upon stock prices is small.[6]

In order to account for the possibility of heteroskedasticity and serial correlation among abnormal returns, equations 3 and 4 were estimated using the GARCH (1,1) procedure. Furthermore, confounding effects were avoided, as well as event clustering unless stocks belong to different industries. Table 3 shows potential event clustering in years 1998-2001, but from Table 2 one may see that only in years 1999 and 2001 there is event clustering. However, it is unlikely to find cross-correlation because in 1999 and 2001 firms belong to different industries and in 2001 they even belong to different countries.

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[5] Other models such as the constant-mean return model and the market-adjusted model were not used because there is no way to account for differences in market integration.

[6] In the presence of substantial currency risk, it would have been better to use the International Capital Asset Pricing Model (ICAPM) analyzed by Bodnar et al. (2003).

Table 3
Tender Offers per Year

	1998	1999	2000	2001	2002	Total
YPF SA		1				1
Banco Rio de la Plata SA			1			1
Telefonica Holding de Argentina SA			1			1
Teleste Celular		1				1
Empresa Bandeirante de Energia SA			1			1
Santa Isabel	1					1
Banco Bhif	1					1
Enersis		1				1
Campos Chilenos		1				1
Gener			1			1
Laboratorio Chile				1		1
Luz del Sur S.A		1				1
Telefonica del Peru SAA			1			1
Cia Minera Atacocha SA				1		1
Banco Continental Peru					1	1
Electricidad de Caracas			1			1
CANTV				1		1
Total	2	5	6	3	1	17

Following the suggestions by many authors, parametric and nonparametric tests were used to detect aggregate abnormal performance. Three parametric tests were used (J1, J2 and J3) and one nonparametric test (J4). The first two tests were used because they have some ability to detect abnormal performance even with small sample sizes, while the BMP test (J3) was used to account for event-induced variance. The generalized sign test (J4) served to account for non-normality in the cross-section of abnormal returns.

A major concern in working with a small sample size is the possibility that one firm (an outlier) drives the results. Figures 3 and 4 in the Appendix show the cumulative abnormal returns for each firm in the sample according to the two models used to estimate abnormal returns (in both figures firms were ordered from left to right). It is not true that positive abnormal returns are present only in one or two firms. In both Figures, more than 80% of the firms report positive cumulative abnormal returns.

Another important problem is the possibility of an increase of the event-induced variance. From figures 5 and 6 (see Appendix), there seems to be an event-induced variance, so one needs to account for this problem. It is also remarkable the similarity among the results of both specifications with and without downside

risk. Although downside risk plays a more important role than total systematic risk within a local market, it seems that its importance diminishes once a situation of partial integration is taken into account.

Tables 4 and 5 (see Appendix) report the statistical significance of average cumulative abnormal returns. Parametric tests J_1 and J_2 show statistically significant positive abnormal returns ranging between 3.1% and 8.2% for one day before and one day after the announcement of the first tender offer. This result is robust across both specifications. Furthermore, the BMP test (J_3) is able to detect positive abnormal returns ranging between 0.18% and 8.2% for different windows mainly before the announcement date. However, abnormal performance due to information linkage is of low magnitude because abnormal returns range between 0.18% and 0.48%. It is worth noting that the partial integration model with downside risk yield more significant abnormal returns than the partial integration model without downside risk.

The performance of the partial integration market model with downside risk even improves when the generalized sign test is used. In this case, the generalized sign test is able to detect not only positive abnormal performance before, but also after the announcement date of a tender offer. Nevertheless, the market overreaction is of low magnitude (0.17%).

In general, the results show a positive abnormal return of about 8% for the announcement date of a tender offer and low positive abnormal returns for the days before and after the announcement date.

Conclusions

Consistent with the previous literature, the results obtained show that tender offers in South America do convey good news to the market in the way of positive abnormal performance for the announcement date. However, the reported abnormal performance (8%) is substantially lower than the one reported by the studies reviewed through the introduction.

The reason for the above result lies in the different views about South American stock markets. In this research, view of partially integrated capital markets rather than the full-segmented view was the preferred. In this scenario stock returns are also sensitive to world events, so abnormal returns cannot be as large as in the case of a full-segmented capital market.

The results also show traces of information leakage and market overreaction. This is consistent with previous literature about stock market efficiency in South American stock markets. For instance, Mongrut (2002) finds short-term

overreaction at the LSE. However, the information linkage seems more robust across model specifications than market overreaction.

The later result is not strange because the days previous to the announcement date of the tender offer are contaminated by the negotiations between the target and the bidder company, and the speculation about the acquisition. Hence, it is likely that some information is filtered to the market.

Although this study has presented evidence of positive abnormal performance surrounding the first announcement of a tender offer, several questions remain unanswered: How to improve the model used in this study to characterize a situation of partial integration? How do abnormal returns are related to the firm ownership concentration? How do they relate to successful and unsuccessful bids? These questions add to a large list of unsolved issues in emerging markets that should be addressed in the near future.

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Figure 3
Cumulative Abnormal Returns by Firm
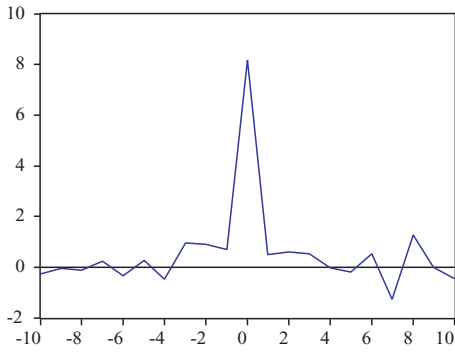**Market Model - Garch**
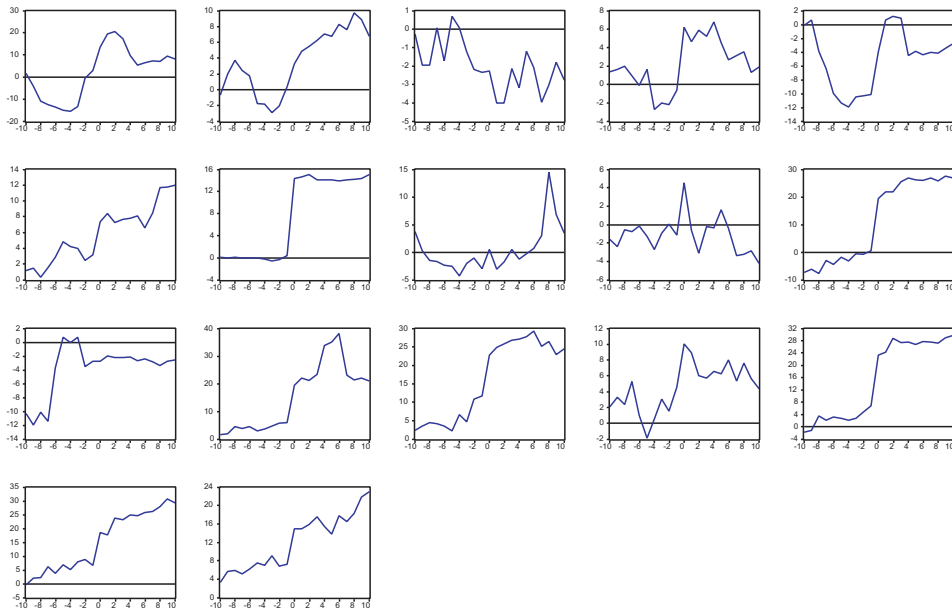
(a) Atacocha	(f) CANTV	(k) Laboratorio Chile	(p) Teleste
(b) Banco Río Plata	(g) Banco Continental	(l) Luz del Sur	(q) YPF
(c) Bandeirante	(h) Electricidad Caracas	(m) Santa Isabel	
(d) Banco Bhif	(i) Enersis	(n) Telefónica Argentina	
(e) Campos Chilenos	(j) Gener	(o) Telefónica Perú	

Figure 4
Cumulative Abnormal Returns by Firm
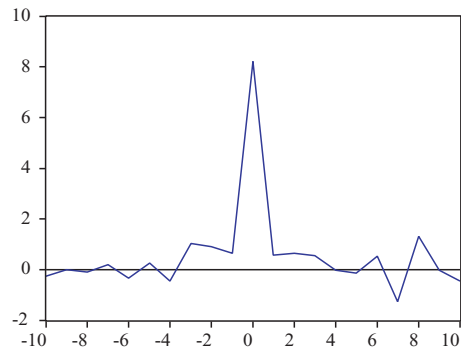**Market Model –Garch– Downside beta**
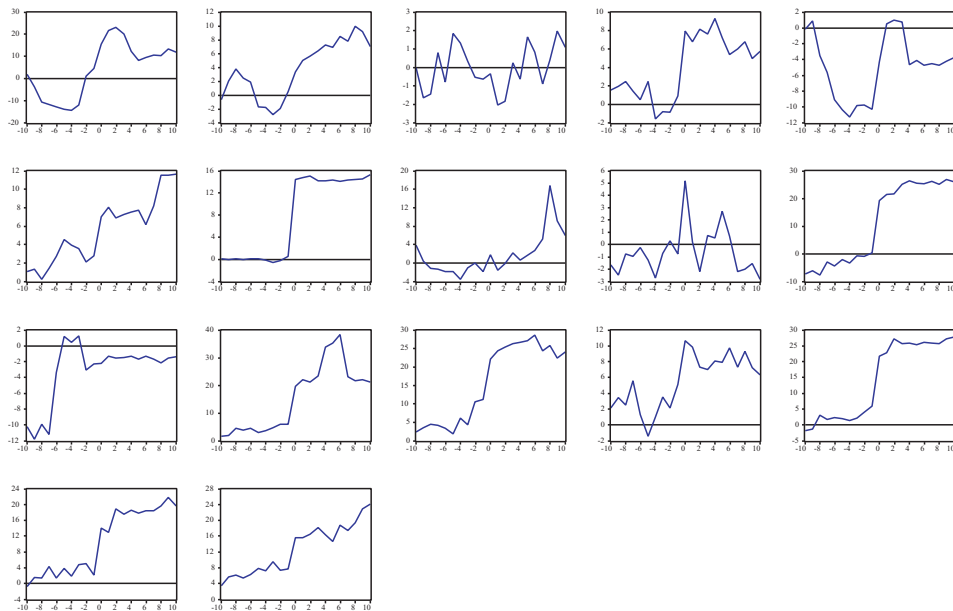
(a) Atacocha   (f) CANTV   (k) Laboratorio Chile   (p) Teleste
(b) Banco Río Plata   (g) Banco Continental   (l) Luz del Sur   (q) YPF
(c) Bandeirante   (h) Electricidad Caracas   (m) Santa Isabel
(d) Banco Bhif   (i) Enersis   (n) Telefónica Argentina
(e) Campos Chilenos   (j) Gener   (o) Telefónica Perú

Figure 5
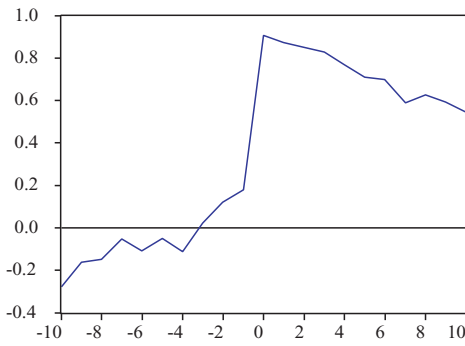**Average Abnormal Returns**
Sample: 17 firms
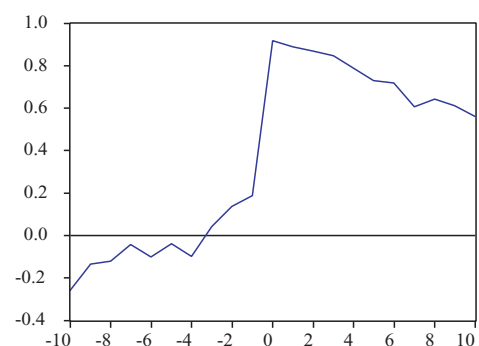

(a) Market Model - GARCH

(b) Market Model - GARCH - Downside beta

Figure 6
Average Cumulative Abnormal Returns
Sample: 17 firms

(a) Market Model - GARCH

(b) Market Model - GARCH - Downside beta

Table 4
Statistical Significance of Average Cumulative Abnormal Returns (CAAR)
Partial Integration Market Model - GARCH (1,1)
(N = 17 firms)

(t_1, t_2)	CAAR (%)	J1	J2	J3	J4
(-10,10)	0.54294	0.70305	0.71237	3.09040***	1.01504
(-5,5)	1.08343	1.29441*	1.18900	2.78262***	3.04512***
(0,0)	8.18108	139.07835***	138.45045***	1.24471	3.04512***
(-1,1)	3.12194	2.91974***	4.17551***	1.55123*	1.52256*
(-10,-1)	0.17821	0.30173	0.43948	1.97609**	0.00000
(-5,-1)	0.46707	0.89619	0.79781	1.87257**	0.00000
(1,10)	0.14386	0.23240	0.41322	-0.01160	0.50752
(1,5)	0.28026	0.52116	0.93904	-0.79183	-0.50752

* Significant at 90% level of confidence.
** Significant at 95% level of confidence.
*** Significant at 99% level of confidence.

Table 5
Statistical Significance of Average Cumulative Abnormal Returns (CAAR)
Partial Integration Market Model - Downside Risk GARCH (1,1)
(N = 17 firms)

(t_1, t_2)	CAAR (%)	J1	J2	J3	J4
(-10,10)	0.56032	0.72580	0.76032	3.57386***	1.97122**
(-5,5)	1.10574	1.32020*	1.25122	3.00266***	3.44964***
(0,0)	8.21012	139.57206***	138.94193***	1.24350	3.44964***
(-1,1)	3.14759	2.94533***	4.31509***	1.56082*	1.97122**
(-10,-1)	0.18783	0.31902	0.46372	2.15453**	0.98561
(-5,-1)	0.47546	0.91376	0.81022	2.37543***	1.47842*
(1,10)	0.16783	0.26999	0.49184	0.40454	1.47842*
(1,5)	0.31515	0.58017	1.06125	0.19473	0.00000

* Significant at 90% level of confidence.
** Significant at 95% level of confidence.
*** Significant at 99% level of confidence.