DOCUMENTO DE DISCUSIÓN

DD/06/02

Is There a Market Payoff for Being Green at the Lima Stock Exchange?

Samuel Mongrut and Jesús Tong

UNIVERSIDAD DEL PACÍFICO
CENTRO DE INVESTIGACIÓN

DOCUMENTO DE DISCUSIÓN

DD/06/02

 DD/06/02

Documento de Discusión

¿Existe un beneficio económico por ser verde en la Bolsa de Valores de Lima?

Elaborado por Samuel Mongrut y Jesús Tong

Enero 2006

Resumen

En contraste con la abundante investigación en mercados desarrollados, existe escasa evidencia empírica sobre la relación entre el desempeño económico y el desempeño medioambiental de empresas en mercados de capitales emergentes. En este trabajo, se muestra evidencia de tal relación para un conjunto de 10 acciones correspondientes a 10 empresas que cotizan en la Bolsa de Valores de Lima. Estas acciones generan rendimientos anormales promedio acumulados que van de 0.7% hasta 1.27% para un día antes y un día después del anuncio de una certificación ISO 14001 por parte de la empresa dependiendo del modelo utilizado para generar los rendimientos anormales. El rendimiento anormal positivo no es producido solo por una empresa y es robusto a través de distintas especificaciones para generar los rendimientos anormales. A pesar de que la baja magnitud del rendimiento anormal positivo indica que los aspectos medioambientales todavía tienen poca importancia para los inversionistas en la Bolsa de Valores de Lima, las empresas en el Perú tienen un incentivo adicional para ser cada día mas verdes.

Palabras claves: ISO 14001, Estudio de Eventos, Sistema de Gestión Ambiental (EMS)

E-mail de los autores: mongrut_sa@up.edu.pe, tong_jj@up.edu.pe

UNIVERSIDAD DEL PACÍFICO
CENTRO DE INVESTIGACIÓN

1. Introduction

Since the publication of the document *ISO 14001 Environmental Management Systems – Specification with guidance for use*, by the International Organization for Standardization (ISO), on September 1st 1996, many firms around the world have adopted the standard as a way to conform with their environmental policy. An environmental policy shows the firm's intentions and commitment to the environment. This policy usually requires firms to prevent pollution, to comply with relevant environmental legislation as well as continually improve their environmental performance. Furthermore, within the framework of ISO 14001, a firm's environmental policy must also be made public.

An Environmental Management System (EMS) is a management tool that provides a framework for practices, procedures and processes to manage *systematically* an organization's environmental agenda. In particular, an EMS is made up of five steps: setting the environmental policy, planning the way to achieve the objectives, implementing and executing the plan (which includes training, awareness, communication, and so on), monitoring and taking corrective action, and reviewing. These five steps define the way to how to continually improve a the environmental performance of a firm. An EMS belongs to the organization's structure and has to achieve, improve and sustain the firm's environmental policy.

The ISO 14001 is the only normative standard in the series of standards. This means that firms can achieve international recognition about their environmental performance by obtaining an ISO 14001 certification, while the other ISO 14000 series are not subject to a third part certification. In other words, investors and other stakeholders may regard the achievement of the ISO 14001 certification as a commitment to an ongoing improvement of the firm's environmental performance.

In this research, the hypothesis is that there is a positive relationship between the achievement of the ISO 14001 certification and the firm's stock returns. The achievement of an ISO 14001 certification signals a commitment to continually improve the firm's environmental performance in the future and this will put the firm in a better competitive position to take advantage of future investment opportunities. The positive expectations about future investment opportunities are discounted back into the firm's stock price, so one must be able to observe positive abnormal returns around the announcement date of an ISO 14001 certification. In fact, there is evidence that EMS help firms to improve their economic and environmental performance although the EMS benefits are not systematically explored by companies (Hamschmidt and Dyllick 2001).

The relationship between the firm's economic and environmental performance is not easy to establish because there are contradictory empirical results. Some studies speak of a positive link between both while others suggest that there is no relationship at all. The inconsistency among empirical results in the literature have been explained by Schaltegger and Synnestvedt (2002). According to these authors, the empirical results are compatible because a good environmental management can produce a positive link, whereas bad environmental management can generate no relationship or even a negative one. Consequently, the way environmental management is conducted determines the relationship between environmental and economic performance.

Schaltegger and Synnestvedt (2002) have proposed two research strategies in order to find out what kind of environmental management results in both a better environmental and economic performance: to conduct in-depth case studies or to study the economic impact of good environmental management. In both cases, the authors are referring to ex post studies about the relationship between a firm's economic and environmental performance. In this research the approach is ex ante, which means that the main issue here is not how environmental management is being conducted and which economic impact it has had. The stress in this research is placed on the impact of the firm's signal to improve its environmental performance in the future (achievement of the ISO 14001 certification) on its stock return (economic performance).

No study could be found so far that focuses specifically on the connection between an ISO 14001 certification and a firm's stock returns in emerging markets. Some studies, though, have related the ISO 9000 certification with the firm's market value. Furthermore, some event studies have been conducted in developed markets like the United States about the relationship between the firm's environmental performance and the firm's economic performance.

Table 1 summarizes the most important findings of six event studies; the first two discuss the relationship between firm's environmental performance and its economic achievements. The other event studies are oriented to study the relationship between a firm's quality performance (signaled by the achievement of the ISO 9000 certification) and its economic performance. Wagner (2001, 2003a) reviews more event studies about the relationship between the firm's environmental and economic performance. However, all the results are in line with the ones reviewed in Table 1. One has chosen to review the studies reported in Table 1 because they seek to determine whether the certification of any ISO standard or the adoption of a strong EMS generates positive abnormal returns around the announcement date.

Table 1: Results of relevant event studies

Study	Major findings
White (1996)	U.S. firms obtain significant positive mean abnormal return of 1.05% for the day after they have signed the CERES principles.
Klassen and McLaughlin (1996)	U.S. firms get significant positive cumulative average abnormal return for strong environmental management (0.63%) and significant negative abnormal returns for a weak environmental management (-0.82%)
Hendricks and Singhal (1996)	U.S. firms reap significant positive mean abnormal returns, from 0.59% to 0.67%, on the date of the announcement of a quality award.
Lima et al. (2000)	There is no relation between quality certification, as indicated by ISO 9001 and ISO 9002, and the economic performance of Brazilian firms.
Nicolau and Sellers (2002)	The Spanish stock market reacts positively to the achievement of quality certification ISO 9000
Corbett et al. (2002)	U.S. firms, after deciding to seek their first ISO 9000 certification, get significant abnormal economic improvements depending on the industry.

From Table 1 significant and positive abnormal returns, ranging between 0.6% and 1%, were obtained around the announcement date of an event indicating a strong EMS. In the case of White's study (1996) the event was the firm's adoption of the Coalition for Environmental Responsible Economies' (CERES) principles, which is a formal code for corporate environmental responsibility.

In the case of Klassen and McLaughlin (1996) the event was the winning of an environmental award given by an independent third party. These authors also found a significant negative cumulative average abnormal return for weak environmental management presented in the form of an environmental crisis (e.g. product recalls, announcement of oil spills, etc.).

The other four studies focused on the relationship between the firm's quality performance and its economic performance. All studies, with the exception of Lima et al. (2000), found a statistically significant and positive relationship between the two. Hendricks and Singhal (1996) studied the effect of winning a quality award on the firm's stock return, while the studies of Nicolau and Sellers (2002) and Corbett et al. (2002) used the achievement of the quality standard ISO 9000 to measure the quality performance.

In the study of Nicolau and Sellers (2002) a firm's stock return is taken as a measure of economic performance, while the Corbett et al. (2002) use four different measures: Return on assets (ROA), Tobin's Q, one internal measure of performance (cost of goods sold/Sales), and one external measure of performance (Sales/Total assets). For all measures, Corbett et al. (2002) found a positive effect of the quality certification with the exception of the internal performance measure for which there is a negative effect.

Overall, there is a positive link, though of low magnitude, between a firm's environmental and economic performance. Besides, there is a positive relationship between the firm's achievement of an ISO 9000 (quality performance) and its economic performance. Given these results, the question arises whether there is a connection between a firm's environmental commitment, embodied in the ISO 14001 certification, and its economic performance. In other words, does the firm's achievement of an ISO 14001 certification yield positive abnormal returns? If there are positive abnormal returns, what are their magnitude? Do they appear long before the announcement date of an ISO 14001 certification? How long do they last? These empirical questions will be addressed in the fourth section.

The remaining part of the paper has been structured in four sections. Important issues related to the proper conduction of event studies are reviewed in the next section. In the third section one discusses the sample criteria and describes the data. The methodology and results are explained in the fourth section and the last section concludes the work.

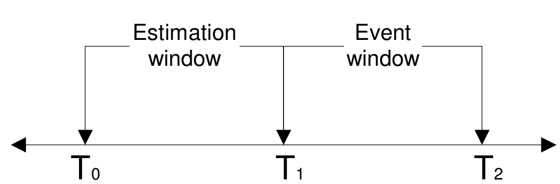
2. Issues in event studies

In conducting event studies there are several issues that one needs to account for. In this section one reviews the main stages of the process emphasizing the problems that one may encounter and the way to deal with them. Five important issues are discussed: event definition, selection criteria, estimation of abnormal returns, estimation of model parameters and tests for detecting abnormal returns. These issues will be discussed separately in the following subsections.

2.1 Event definition

It is crucial to identify the event subject to scrutiny (e.g. the announcement date of a merger, an acquisition, an earnings announcement, a change in the debt rating, the achievement of an ISO standard, etc). Then, one must obtain the exact date of the event to determine the estimation and event windows (see Figure 1).

Figure 1: Event study windows



The event date, when the announcement occurs, lies somewhere within the interval [T1+1, T2], which is the event window with length L_2=T2-T1-1, while the interval [T0+1, T1] is the estimation window with length L_1=T1-T0-1. During the estimation window one calibrates different models for abnormal returns. These models are then used during the event window in order to estimate realized abnormal returns around the announcement date. When the study is being conducted with daily data, the estimation window usually ranges between 100 and 300 trading days (Peterson 1989). The length of the event window usually depends on the ability to fix precisely the announcement date. If one is able to date it with precision, the event window will be short and the tests to detect abnormal returns will be more powerful. The length of the event window normally ranges between 21 and 121 days (Peterson 1989).

2.2 Selection criteria

This step is certainly a very important one since it is easy to introduce a selection bias in the definition of the sample of firms to be studied. In emerging markets, one of the main tradeoffs is between having quantitatively more firms in the sample, but with several firms subject to thin trading or having less firms in the sample, but actively traded. In the former case, one needs to use a procedure to test for abnormal returns in the presence of thin trading, while in the later case one has to avoid as much as possible any selection bias in the sample. This tradeoff has to be made because of the low number of actively traded or liquid stocks in emerging markets.

Table 2: Liquid firms as a percentage of total traded stocks
Period: 1995-2003

Year	Argentina	Brasil	Chile	Peru	Colombia	Venezuela
1995	51	25	38	30	19	34
1996	53	27	37	29	12	52
1997	58	30	32	24	16	58
1998	49	22	21	22	15	40
1999	45	31	27	18	11	29
2000	36	30	23	13	4	27
2001	26	27	22	8	8	21
2002	35	27	19	10	21	n.a.
2003	55	30	23	15	32	18
Average	**44**	**28**	**26**	**17**	**13**	**32**

n.a. not available
Source: Mongrut S. (2004)

As Table 2 shows, the percentage of actively traded stocks (with a market presence of at least 75%), as a fraction of the total number of traded stocks per year, ranged between 8% and 30% at the LSE during the period 1995-2003. The situation for other South American emerging markets is similar.

Thin trading or nonsynchronous trading means that market shocks will not be incorporated immediately into the price of the stock simply because it is not being traded. If one does not consider the effect of thin trading, 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 beta parameters of actively traded stocks. This bias arises because time series of stock prices are recorded at time intervals of one length when in fact they are incurred 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 give 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) in testing abnormal returns.

What happens if one takes the option to include in the sample few actively traded firms? 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). Besides, even in the presence of abnormal returns that do not obey a normal distribution, one can still use parametric tests invoking the Central Limit Theorem. The real problem is the potential for a selection bias.

2.3 Estimation of abnormal returns

In this section, one only introduces three models to estimate abnormal returns: the constant-mean return model, the market model, and the market adjusted model. According to Brown and Weinstein (1985) there is little value to gain in using a multifactor model (such as the Arbitrage Pricing Theory-APT) versus the market model because the later model seems to be the more suitable to detect abnormal performance (Dyckman et al. 1984).

2.3.1 The constant-mean return model

By using this model one assumes that the stock's mean return of the estimation window will remain constant during the event window. For each stock "i" in period "t", the abnormal return is estimated as the difference between the realized return "$R_{i,t}$" and the mean return:

$$AR_{i,t} = R_{i,t} - \bar{R}_i \tag{1}$$

Where the mean return is given by:

$$\bar{R}_i = \frac{1}{L_1} \sum_{t=T_0+1}^{T_1} R_{i,t} \tag{2}$$

In this model, as well as in the following ones, continuously compounded returns are defined in the following way ("$P_{i,t}$" is the price of stock "i" in period "t"):

$$R_{i,t} = Ln\left(P_{i,t}\right) - Ln\left(P_{i,t-1}\right) \tag{3}$$

Therefore formulas 1 and 2 consider the mean return as an arithmetic average rather than a geometric one. Furthermore, in the presence of thin trading one must apply the following simple rule: if one daily quote is missing, this one and the quote for the subsequent day must be excluded from the estimation of returns.

As shown by Brown and Warner (1985), the constant-mean return model yields similar results to those obtained by using the market model. According to Campbell et al. (1997) the lack of sensitivity to the model choice is due to the fact that the constant-mean return model does not reduce in a meaningful way the variance of abnormal returns.

2.3.2 The market model

The market model is the most common choice to model abnormal returns. This model states that the stock "i" abnormal return in period "t" is equal to:

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t}) \tag{4}$$

As can be observed, the market model adjusts for the stock's systematic risk in estimating the stock abnormal return. In this way, the variance of the abnormal return will be reduced because one is removing the portion of the return that is related to the market index "$R_{m,t}$" (MacKinlay 1997). Popular choices for the market index are the equally weighted local market index and the value weighted local market index. However, the former index is more likely to detect abnormal returns because it has been shown that it has more correlation with market returns (Peterson 1989).

Usually, the model parameters (alpha and beta) are estimated during the estimation window using Ordinary Least Squares (OLS). The OLS estimation of equation 4 relies on two crucial assumptions concerning the error term or abnormal return: the variance of the abnormal return is constant through time and there is no time series correlation among the abnormal returns. In other words, the model implies no heteroskedasticity and no autocorrelation. Nevertheless, thin trading could generate times-series dependence or serial correlation. Furthermore, a variance increase due to the event announcement generates the problem of heteroskedasticity. If one uses the variance of the estimation window instead of the variance of the event window, the tests statistics will yield too many rejections of the null hypothesis that the cumulative average abnormal return is equal to zero.

One way to correct for serial correlation and heteroskedasticity in abnormal returns is to estimate the model parameters using the Generalized Autoregressive Conditionally Heteroskedastic Model (GARCH). The GARCH (1,1) is expressed in the following way:

$$\begin{aligned} AR_{i,t} &= R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t}) \\ AR_{i,t} &= \rho_i AR_{i,t-1} + \varepsilon_{i,t} \\ h_{i,t} &= \omega_{i,0} + \omega_{i,1}\varepsilon^2_{i,t-1} + \omega_{i,2} h_{i,t-1} \end{aligned} \tag{5}$$

Where:

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

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

$R_{m,t}$: Return of the local market index in period “t”

ρ_i: First-order correlation coefficient of stock “i”

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 the returns are considerable more skewed and leptokurtic than in developed markets (Mongrut 2004 and 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 (1950) procedure proposed by Dombrow et al. (2000) or to use a non-parametric test to test for abnormal returns such as the generalized sign test analyzed by Cowan (1992) or the rank test proposed by Corrado (1989). In this research one uses both alternatives.

Dombrow et al. (2000) suggested the use of the Theil (1950) nonparametric regression technique in order to correct for non-normality in the estimation of the market model parameters. In fact, they report that a combination of the Theil’s technique and a nonparametric test statistic improves the power in the detection of abnormal returns. Furthermore, Theil’s estimators perform better than OLS estimators when abnormal returns are non-normal (Talwar 1993).

The Theil’s approximate method follows five steps for the “j” pair of observations that belong to the estimation window:

1. Sort the pairs of returns $(R_{i,t}, R_{m,t})$ in ascending order based on the values of $R_{m,t}$.
2. Separate the data pairs in two groups based upon the median (do not consider the median pair if it is odd).

3. Calculate the following slope parameter for each of the N/2 data pairs in each group with the following expression:

$$\beta_{\left(j,j+\frac{N}{2}\right)} = \frac{R_{\left(j+\frac{N}{2}\right)} - R_j}{Rm_{\left(j+\frac{N}{2}\right)} - Rm_j} \qquad \text{For: } j = 1 \text{ to } \frac{N}{2} \tag{6}$$

   Where N is the number of data items.

4. Sort the calculated slope parameters in ascending order. The stock beta ($\hat{\beta}_i$) equals the median slope.

5. Using the slope (beta) parameters of the previous step, calculate the values of alphas for all data pairs. The stock alpha ($\hat{\alpha}_i$) equals to the median value of alphas.

As indicated by Dombrow et al. (2000) focusing on the median estimates eliminates the possibility that outlier observations will affect the estimation of the model parameters. In this sense, one gets more robust estimators for the parameters.

One of the features of non-normality is the fact that stock returns in emerging markets are right skewed. In this sense, many authors have argued that investors in emerging markets care more about downside (systematic) risk than traditional systematic risk (Estrada 2000). In this sense, Estrada (2002) has proposed an equilibrium model that accounts for downside risk named 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 traditional beta from the CAPM. Following this argument, the ex post version of the D-CAPM can be used to estimate abnormal returns in emerging markets:

$$AR_{i,t} = Min\left[\left(R_{i,t} - \overline{R}_i\right), 0\right] - (\hat{\alpha}_i + \hat{\beta}_i^D Min[(R_{m,t} - \overline{R}_m), 0]) \tag{7}$$

Where:

$\overline{R}_m$: Mean return of the market index

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

β_i^D : Downside beta of stock "i"

2.3.3 The market-adjusted model

Abnormal returns under the market-adjusted model can be written as follows:

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{8}$$

Another way to consider this model is to start from the market model (equation 4) and impose the restrictions of alpha equal to zero and beta equal to one. In this sense, the model does not require an estimation window to estimate model parameters. As noted by Campbell et al. (1997) this model is suitable whenever there is no estimation window available. Due to the fact that the above restrictions may not apply in emerging markets, it is recommended to use this model jointly with other models.

2.4 Tests for abnormal returns

Once the abnormal returns have been estimated for each stock, using one or more models, one must test whether abnormal returns are statistically different from zero 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 different from zero, while the test for a time interval aims to determine whether the cumulative average abnormal returns during a selected time interval for a group of stocks are statistically different from zero.

In this research, one uses three parametric tests (J1, J2 and J4) and one nonparametric test (J3). Parametric tests rely on a known probability distribution, usually a Normal or T-Student distribution, while nonparametric tests do not. The parametric test J1 aims to determine whether the cumulative average abnormal return differs from zero within the selected time interval [t1,t2] (MacKinlay 1997 and Campbell et al. 1997). The test J1 is suitable whenever one considers that cumulative abnormal returns vary across securities. If this is the case, one must give equal weight to the realized cumulative abnormal return of each security.

$$J_1 = \frac{CAAR(t_1,t_2)}{\left[Var\left(CAAR(t_1,t_2)\right)\right]^{\frac{1}{2}}} = \frac{CAAR(t_1,t_2)}{\left[\frac{1}{N^2}\sum_{t=t_1}^{t_2}\sum_{i=1}^{N} S_{i,\varepsilon}^2\right]^{\frac{1}{2}}} \qquad J_1 \stackrel{a}{\sim} N(0,1) \qquad (9)$$

Where:

$$CAAR(t_1,t_2) = \sum_{t=t_1}^{t_2} AAR_t \text{ and } AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$$

$CAAR(t_1,t_2)$: Cumulative average abnormal return for the time interval (t_1,t_2)

AAR_t: Average abnormal return for period "t"

Another possibility would be to consider constant abnormal returns across securities. In this case it is more appropriate to use J2 because it gives more weight to the securities with the lower abnormal return variance so that the power of the test will improve.

$$J_2 = \frac{SCAAR(t_1,t_2)}{\left[\left(\frac{1}{N}\right)\frac{L_1-2}{L_1-4}\right]^{\frac{1}{2}}} \qquad J_2 \stackrel{a}{\sim} N(0,1) \qquad (10)$$

Where:

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

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

$$CAR_i(t_1,t_2) = \sum_{t=t_1}^{t_2} SAR_{i,t} \text{ and } SAR_{i,t} = \frac{AR_{i,t}}{S_{i,\varepsilon}}$$

$SCAAR(t_1,t_2)$:	Average standardized cumulative abnormal return for the event window [t1,t2]
$SCAR_i(t_1,t_2)$:	Standardized cumulative abnormal return for stock "i" for the event window [t1,t2]
$CAR_i(t_1,t_2)$:	Cumulative abnormal return for stock "i" for the event window [t1,t2]
$SAR_{i,t}$:	Standardized abnormal return for stock "i" in period "t"
$S_{i,\varepsilon}$:	Standard error of the estimate for stock "i"

If the variance of abnormal returns increases on the event date, the above parametric tests will reject the null hypothesis more often than the nominal significant level (Cowan and Sergeant 1996). In other words, event-induced variance increases cause parametric tests to report a price reaction more often than expected (Cowan 1992). To avoid this problem, one may use the Boehmer et al. (1991) test or better known as the BMP test:

$$J_4 = \frac{\sum_{i=1}^{N} SCAR_i(t_1,t_2)}{\left[Var\left(SCAR(t_1,t_2)\right)\right]^{\frac{1}{2}}} \tag{11}$$

Where:

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

Due to the fact that the BMP test works with data from the event window, it can consider any event-induced variance increase 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).

With respect to the problem of the non-normality in stock returns, one may use a nonparametric test, which does not rely on this assumption. Two nonparametric tests are available: the generalized sign test or the rank test. In general the 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. Hence, due to the possibility of event-induced variance increase, one has favored the generalized sign test over the rank test in this research. Besides, in the presence of non-normality both tests are well specified and equally powerful in detecting abnormal performance.

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 window 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 1 whenever there is a positive abnormal return for security "i" on day "t", otherwise is 0. Now, if one defines "ω" as the number of securities in the event window with a positive cumulative abnormal return, one may write the generalized sign test statistic (S) in the following way:

$$J_3 = \frac{\omega - N\hat{p}}{\left[N\hat{p}(1-\hat{p})\right]^{\frac{1}{2}}} \qquad \text{Where: } J_3 \sim N(0,1) \qquad (12)$$

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

3 Sample criteria and data description

Before going into the details of the selected sample, it is important to know some features of stock returns at the Lima Stock Exchange (LSE). It has already been pointed out that stock returns in emerging markets are characterized by being non-normal. As Table 3 shows, this feature applies to the LSE and is shared by the main South American capital markets. In particular, stock returns at the LSE are right skewed and they exhibit excess kurtosis.

Table 3: Statistics for stock indexes in South American capital markets

Statistic	Argentina *	Brasil *	Chile *	Peru **	Colombia **	Venezuela **
Mean (Annualized)	13.0%	11.7%	12.3%	9.8%	3.3%	2.4%
Median (Annualized)	13.8%	26.4%	8.9%	15.2%	6.1%	-1.9%
Maximum (Monthly)	67.0%	59.5%	19.5%	30.4%	26.5%	48.0%
Minimum (Monthly)	-48.6%	-110.7%	-34.4%	-41.0%	-27.6%	-63.8%
Variance (Annualized)	29.2%	36.6%	6.6%	10.2%	10.4%	27.9%
Skewness	0.640	-1.335	-0.398	-0.593	-0.213	-0.795
Kurtosis	3.632	8.910	2.094	3.245	0.882	3.606

Source: Mongrut (2004)
* Period: January 1987 – June 2004
** Period: January 1993 – June 2004

With respect to the selected sample, Mongrut and Tong (2004) reported a total of 42 firms where an EMS has been implemented in Peru. Of them, 30 firms adopted the ISO 14001 certification during the years 1995-2003, but only 14 were traded at the LSE. These 14 firms were then filtered on three criteria: they should have a minimum of 245 daily quotations before the announcement date of an ISO 14001 certification, they should have a minimum of 31 daily quotations after the announcement date, and they shouldn't be exposed to a different events during the event window. As Table 4 shows, only 10 firms fulfilled these criteria.

This sample criterion helped to remove some thin traded firms from the sample. However, there were still some missing returns for the estimation window. In this case, the missing quote and the succeeding period quote were removed from the analysis. This method, proposed by Brown and Warner (1985), attains the greatest sample size without affecting the identification of the abnormal performance (Peterson 1989). Finally, confounding effects were avoided due to the third criteria.

Table 4: Data description

Firm	Quotations previous to the announcement date	Quotations after the announcement date	Announcement Date
CERVESUR	398	384	06/22/1998
MILPO	649	267	04/06/1999
BACKUS	1255	411	12/11/1999
ALICORP	602	288	07/14/2000
VOLCAN	790	519	07/27/2001
GOODYEAR	1039	81	01/30/2002
MALTERIA LIMA	681	31	02/28/2002
BUENAVENTURA	1562	376	04/22/2002
DUKE ENERGY	2309	84	07/17/2003
ELSA	394	31	08/06/2003

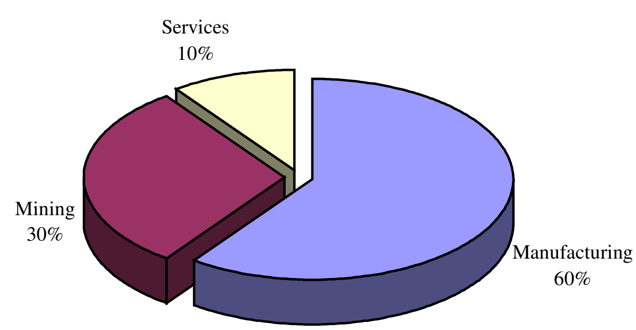
Sources: Economatica and Centro de Desarrollo Industrial (CDI)

The fact that one considers only firms who voluntarily adopted the ISO 14001 certification can produce a selection bias. If one selects randomly the sample of certified firms from the total population of firms, there is no reason to suspect that they have some unobserved and observed characteristics that have influenced them to adopt such standard. However, if one does not follow a random selection process, it may be that common unobserved and observed characteristics (e.g. size, industry sector, etc) influence the decision to adopt the ISO 14001 certification. In this later case, one cannot draw inferences for the total population of firms. For instance, one cannot state that because this sample of firms earns abnormal returns on the announcement date of an ISO 14001 certification other firms are able to earn them too.

A raw attempt to identify a potential selection bias is to compare the selected sample of firms with another sample, which does not have an ISO 14001 certification granted. One choice would be to use firms with EMS, but without such certification granted. Out of the 42 firms with EMS, 12 did have EMS and were not certified. Unfortunately, these firms were not traded at LSE.

How severe could the potential selection bias be? There is no precise way to assess this, but it is unlikely that this bias is present in the sample of firms. As Figure 2 shows, the firms belong to different business sectors. Besides this, the selected firms have different sizes (not reported).

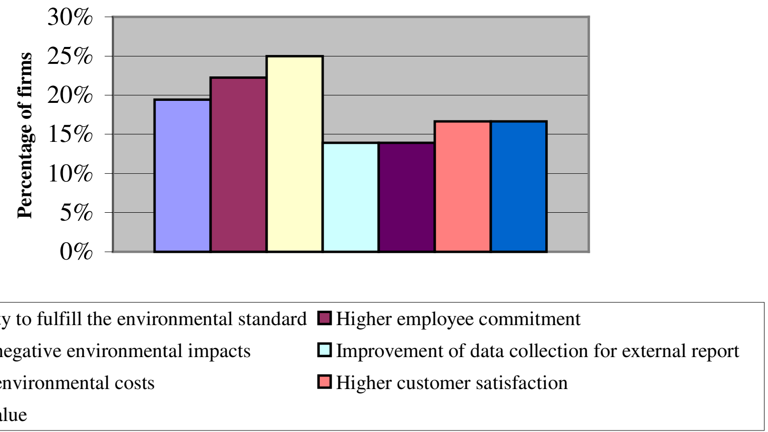
Figure 2: Certified firms by sector



Source: Own elaboration with data collected from Mongrut and Tong (2004)

What about non-observable or soft firm characteristics? Figure 3 shows the perceived benefits of implementing an EMS according to nine firms that belong to the selected sample. As one can see, preferences are almost equally divided among the various benefits. The most important benefits are the reduction of negative environmental impacts and the achievement of a higher employee commitment. The former benefit is related to external stakeholders, while the later one is related to internal stakeholders.

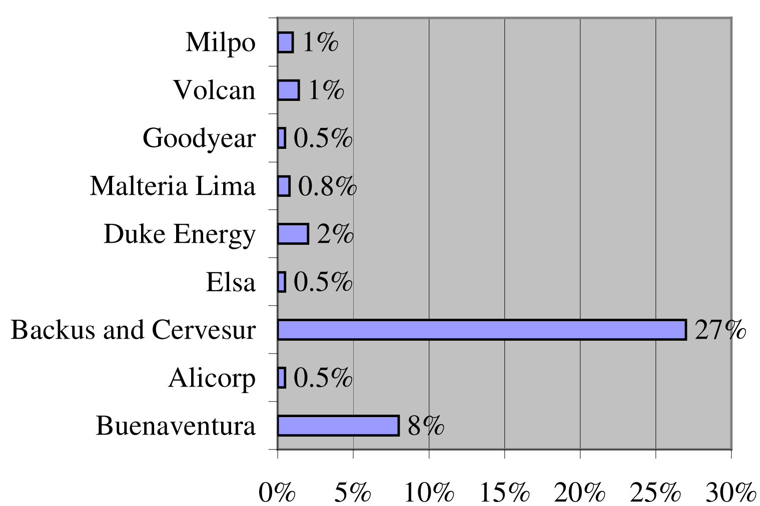
Figure 3: Benefits from implementing an Environmental Management Systems (EMS)

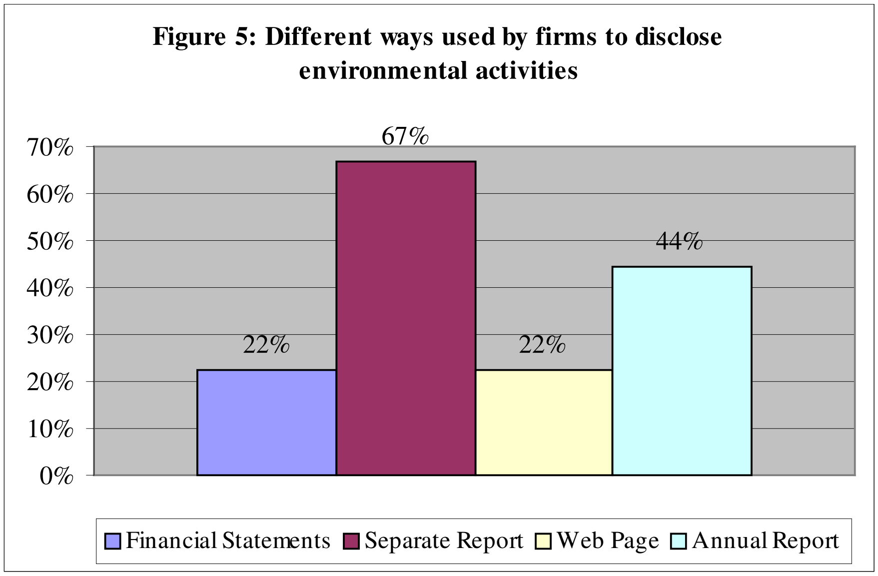


Source: Own elaboration with data collected from Mongrut and Tong (2004)

Another way to check for unobserved firm characteristics is to determine how many pages of the annual report are dedicated to the issue of sustainable development. As Figure 4 shows, nine firms devote a different number of pages to sustainable issues. However, this is just a broad indicator because firms can use different ways to report about their environmental activities (see Figure 5).

Figure 4: Percentage of annual report pages dedicated to sustainable development





Source: Own elaboration with data collected from Mongrut and Tong (2004)

From the above discussion, it is unlikely that firms in the selected sample share common observable and unobservable features that makes them more prone to adopt an ISO 14001 standard.

4 Methodology and results

In this section one explains briefly the different steps used in this research to determine the daily abnormal performance of the selected sample of firms. The event under study is the announcement of the first ISO 14001 certification as signal of firm's commitment to a substantial improvement in its environmental performance. In this sense, one may expect positive abnormal returns on the announcement date of such certification.

It has been considered an estimation window of 214 days and an event window of 60 days around the announcement date (30 days previous and 30 days after the announcement date). This implies a total of 275 daily stock returns. With this general event window some abnormal performance could be captured, and even more important, the estimation window could be isolated from the event window. This general event window was then restricted by aggregating abnormal returns for different shorter time intervals.

As discussed previously, parametric tests rely on the assumption that abnormal returns are normally distributed so that inferences about the aggregate abnormal performance can be made. For the selected sample, stock returns and estimated abnormal returns are not normally distributed because most of them are skewed and leptokurtic (not reported). As noted before, whenever abnormal returns are non-normally distributed, one may still rely upon asymptotic results by applying the central limit theorem.

Brown and Warner (1985) have shown that tests converge quickly to their asymptotic values, even with samples of size 5 parametric tests statistics are still well specified. However, a problem is that the degree of skewness increases in small sample sizes so stated significant levels should not be taken literally (Brown and Warner 1985). A way to account for this problem is to use a combination of the Theil's method for the estimation of the market model's parameters and the application of a nonparametric test such as the generalized sign test. Furthermore, in this research one accounts directly for skewness by estimating a downside-risk version of the market model.

Another problem that one must deal with is event clustering. Aggregating abnormal returns requires that the different event windows do not overlap in calendar time. When the event windows do overlap covariances between abnormal returns will not be zero and parametric tests are not longer valid. Table 5 shows the year of the first ISO 14001 certification for each firm in the sample.

Table 5: Years of the first ISO 14001 certification

FIRM	98	99	00	01	02	03	Total
CERVESUR	1						1
MILPO		1					1
BACKUS		1					1
ALICORP			1				1
BUENAVENTURA					1		1
GOODYEAR					1		1
ELSA						1	1
MALTERIA LIMA					1		1
DUKE ENERGY						1	1
VOLCAN				1			1
Total	1	2	1	1	3	2	10

A simple inspection of Table 5 leads to the conclusion that potential event clustering may arise in years: 1999, 2002, and 2003. However, after looking at Table 4, one concludes that the clustering problem may occur only in year 2003 because event windows do overlap during 12 days. Nevertheless, the overlapping effect is not likely to induce a serious cross-correlation effect because firms (Duke Energy and ELSA), whose event windows do overlap, belong to different sectors. In fact, Duke sells energy, while ELSA sells beverages.

The time series of abnormal returns were obtained using the constant-mean return model, the market-adjusted model and the market model. In the case of the market model, the parameters were estimated using the GARCH (1,1) procedure, the downside-risk GARCH (1,1) procedure, and the nonparametric regression procedure of Theil. The first procedure corrects for heteroskedasticity and serial correlation in abnormal returns, the second procedure accounts for much of the same with special focus in skewness, while the third procedure corrects for the non-normality in abnormal returns.

As suggested by Zivney and Thompson (1989), a good strategy is to report parametric and nonparametric tests when testing the statistical significance of abnormal returns. In order to assess the statistical significance of the aggregated abnormal performance, three parametric tests (J_1, J_2 and J_4) and one nonparametric test (J_3) have been used:. The first two tests were selected because they have some ability to detect abnormal performance even with small sample sizes. The third test was selected to account for any event-induced increase in variance and the nonparametric test was added 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 6-10 in the appendix show the cumulative abnormal returns for each firm in the sample, and according to the five specifications for estimating abnormal returns (Figures read from left to right). One cannot state that positive abnormal returns are only present in a few firms, in fact more than 7 firms in the sample report positive cumulative abnormal returns across different model specifications.

Another important issue was to identify a potential for event-induced increase in variance. From Figure 11 in the appendix, there seems to be an event-induced variance increase. Alternatively, one may arrive to this observation by looking at the average cumulative abnormal returns (see Figure 12 in the appendix).

Tables 5-A and 5-B in the appendix show the statistical significance of the average cumulative abnormal returns (CAAR) for the sample of 10 firms across the five specifications for estimating abnormal returns (note that CAAR are in decimals, so they must be multiplied by 100% to obtain percentages). In general the constant-mean return model, the market-adjusted model and the downside-risk GARCH (1,1) models do not have a very good performance because they report negative average cumulative abnormal returns for some time intervals. Nevertheless, they also report positive average cumulative abnormal returns of about 0.8% for one day previous and one day after the announcement of the first ISO 14001 certification. This positive abnormal return is statistically significant with parametric and nonparametric tests.

The Theil procedure attains a better performance than the former specifications. With the Theil specification one is able to detect an abnormal performance of 1.27% for one day previous and one day after the announcement date of the first ISO 14001 certification, which is statistically significant with parametric tests. Besides, this specification also reports an abnormal performance of about 0.72% for the announcement date according to the nonparametric test. The market model estimated with GARCH (1,1) yields similar results. It reports a positive abnormal performance of about 0.95% for a time interval of one day previous and one day after the announcement date and it is statistically significant with parametric and nonparametric tests.

One is able to detect some traces of information leakage using the generalized sign test with the GARCH (1,1) specification and with the Theil procedure for days [-5,-1]. However, it is of very low magnitude. In contrast, traces of market overreaction are stronger. Using the GARCH (1,1) and the Theil specifications, one observes positive cumulative abnormal returns up to 1.24% for the time interval [1,5]. This abnormal performance is statistically significant even considering a possible event-induced increase in variance.

5 Conclusion

Overall results indicate a positive abnormal performance around the announcement of the first ISO 14001 certification. The payoffs for being green are usually of low magnitude because investors are just starting to be aware about the importance of environmental issues. Of negative influence is also the fact that one needs to account for transaction costs. According to the Emerging Markets Factbook (1998) transaction costs are of about 76 basis points (0.76%) at the LSE, so net abnormal returns could decrease to about 0.51%.

In a recent paper Wagner (2003b) finds no relationship between the certification of an environmental standard (such as the EMAS or the ISO 14001) and the ex post economic performance of a sample of firms from the Netherlands, Italy, Germany, and the UK. This result depends on the kind of environmental management (Schaltegger and Synnestvedt 2002). Given the type of event study conducted in this research, the relationship between expected environmental performance (signaling) and economic performance has been established only in the short run. The abnormal stock market performance can only be sustained in the long run through a good environmental management that is able to improve the economic performance of the firm.

Although, the results show no evidence of information leakage, they show evidence for market overreaction. The lasting short-term positive abnormal performance is consistent with the literature about stock market efficiency in emerging markets, for instance, Mongrut (2002) finds short-term market overreaction at the LSE.

As expected, the market model estimated with the GARCH (1,1) procedure and the one estimated with the Theil procedure showed a better ability to detect abnormal returns. The reason for this lies in the fact that both specifications consider some features of stock returns in emerging markets such serial correlation, heteroskedasticity and non-normality.

Despite these results, several interesting questions remain for future research: Are investors well-informed about the environmental activities of the firms they invest in? What type of environmental management is consistent with shareholder maximization? What are effective ways to inform investors about environmental activities? Do investors penalize firms that have generated an environmental crisis in emerging markets? Do abnormal performance differ across industries or time? In order to answer these questions one needs to collect information that it is not readily available in emerging markets. To obtain such data is a big challenge that researchers of these markets must face.

To sum up, one may expect that as the LSE becomes more integrated with other capital markets investors will become more aware about the importance of the firms' environmental performance and the net positive abnormal performance will increase in the future at least in the short-term.

6 References

Bekaert G., C. Erb, C. Harvey, and T. Viskanta (1998) Distributional characteristics of emerging market returns and asset allocation. *Journal of Portfolio Management*, 102-116.

Boehmer E., J. Musumeci, and A. Poulsen (1991) Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics 30*, 253-272.

Brown S. and J. Warner (1985) Using daily stock returns: The case of event studies. *Journal of Financial Economics 14*, 3-31.

Brown S. and M. Weinstein (1985) Derived factors in event studies. *Journal of Financial Economics 14*, 491-495.

Campbell J., A. Lo and C. MacKinlay (1997) The econometrics of financial markets. Princeton University Press. New Jersey.

Cohen H., G. Hawawini, S. Maier, R. Schwartz, and D. Whitcomb (1983) Estimating and adjusting for the intervalling effect bias in beta. *Management Science 29*, 135-148.

Corbett Ch., M. Montes and D. Kirsch (2002) The financial impact of ISO 9000 certification: An empirical analysis. Working paper, The Anderson School at UCLA.

Corrado C. (1989) A nonparametric test for abnormal security-price performance in event studies. *Journal of Financial Economics 23*, 385-395.

Cowan A. (1992) Nonparametric event study tests. *Review of Quantitative Finance and Accounting 2*, 343-358.

Cowan A. and A. Sergeant (1996) Trading frequency and event study test specification. *Journal of Banking and Finance 20*, 1731-1757

Dyckman T., D. Philbrick, and J. Stephan (1984) A comparison of event study methodologies using daily stock returns: A simulation approach. *Journal of Accounting Research 22*, 1-30.

Dimson E. (1979) Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics 7*, 197-226.

Dombrow J., M. Rodríguez, and C. Sirmans (2000) A complete nonparametric event study approach. *Review of Quantitative Finance and Accounting 14*, 361-380.

Emerging Markets Factbook (1998) Elkins & McSherry Global Universe fourth quarter 1998.

Fama E. (1976) Foundations of finance. New York: Basic Books, Inc.

Hamschmidt J. and T. Dyllick (2001) ISO 14001: Profitable? Yes! But it is eco-effective? *Greener Management International 34*, 43-54.

Hendricks K. and V. Singhal (1996) Quality awards and the market value of the firm: An empirical investigation. *Management Science 42*, No 3, 415-436.

Klassen R. and C. McLaughlin (1996) The impact of environmental management on firm performance. *Management Science 42*, No 8, 1199-1214.

Lima M., M. Resende and L. Hasenclever (2000) Quality certification and performance of Brazilian firms: An empirical study. *International Journal of Production Economics 66*, issue 2, 143-147.

MacKinlay C. (1997) Event studies in economics and finance. *Journal of Economic Literature 35*, No 1, 13-39.

Mongrut S. (2002) Market efficiency: An empirical survey in Peru and Other Selected Countries. *Apuntes 51*, segundo semestre, 49-85.

Mongrut S. (2006) Tasas de descuento en Latinoamérica: hechos y desafíos. Working Paper, CIUP, Universidad del Pacífico.

Mongrut S. and J. Tong (2006) Environmental reporting through financial statements: The Peruvian evidence. Working Paper, CIUP, Universidad del Pacífico.

Nicolau J. and R. Sellers (2002) The stock market's reaction to quality certification: Empirical evidence from Spain. *European Journal of Operations Research 142*, issue 3, pp. 632-641.
Peterson P. (1989) Event studies: A review of issues and methodology. *Quarterly Journal of Business and Economics 28*, issue 3, 36-66.

Schaltegger S. and T. Synnestvedt (2002) The link between green and economic success: environmental management as the crucial trigger between environmental and economic performance. *Journal of Environmental Management 65*, 339-346.

Scholes M. and J. Williams (1977) Estimating betas from nonsynchronous data. *Journal of Financial Economics 5*, 309-327.

Talwar P. (1993) A simulation study of some nonparametric regression estimators. *Computational Statistics and Data Analysis 15*, 309-327.

Theil H. (1950) A rank invariant method of linear and polynomial regression analysis. I, II, and III *Nederlandse Akademische Wetenschappen Proc. 53*, 386-392, 521-525, and 1897-1912.

Wagner M. (2001) A review of empirical studies concerning the relationship between environmental and economic performance: What does the evidence tell us? Center for Sustainability Management, University of Lueneburg.

Wagner M. (2003a) How does it pay to be green? An analysis of the relation between environmental and economic performance at the firm level and the influence of corporate environmental strategy. Tectum Verlag. University of Lüneburg.

Wagner (2003b) The influence of ISO 14001 and EMAS certification on environmental and economic performance of firms: an empirical analysis. In M. Bennett, P. Rikhardsson and S. Schaltegger (Eds.) *Environmental Management Accounting - Purpose and Progress*, 367-386, Kluwer Academic Publishers.

White M. (1996) Corporate environmental performance and shareholder value. University of Virginia Charlottesville, V.A: McIntire School of Commerce.

Zivney T. and D. Thompson (1989) The specification and power of the sign test in measuring security price performance: Comment and analysis. *The Financial Review 24*, 581-588.

Figure 6-1
Cumulative abnormal returns by firm
Constant-mean return model

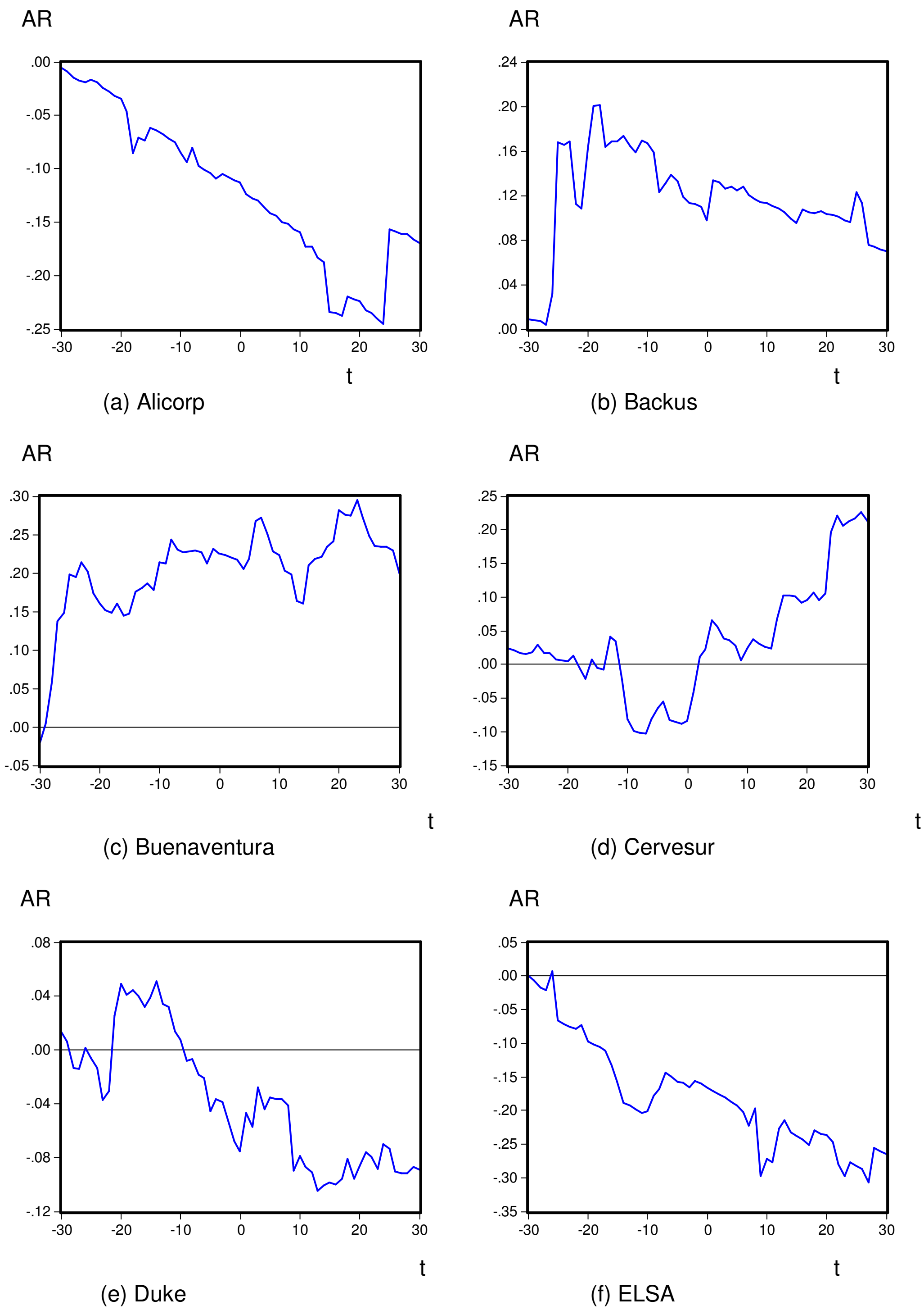
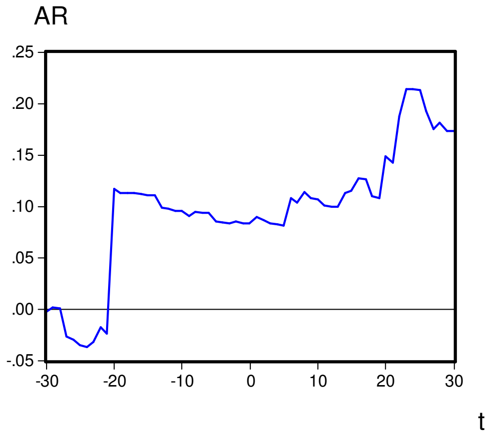
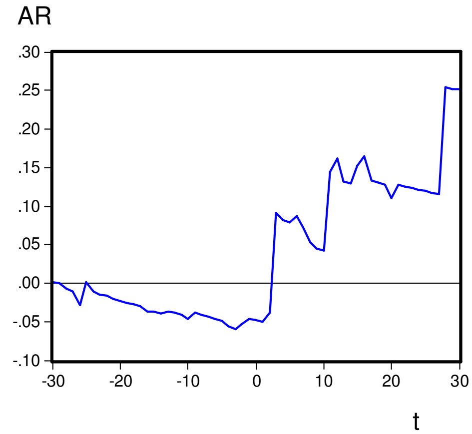


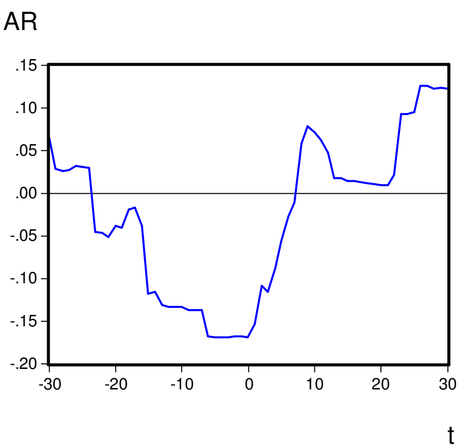
Figure 6-2
Cumulative abnormal returns by firm
Constant-mean return model



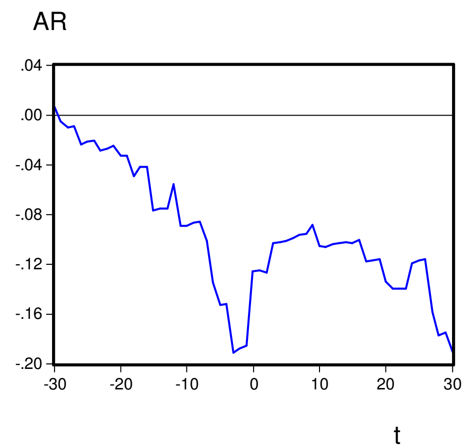
(g) Goodyear



(h) Maltería Lima



(i) Milpo



(j) Volcan

Figure 7-1
Cumulative abnormal returns by firm
Market-adjusted model

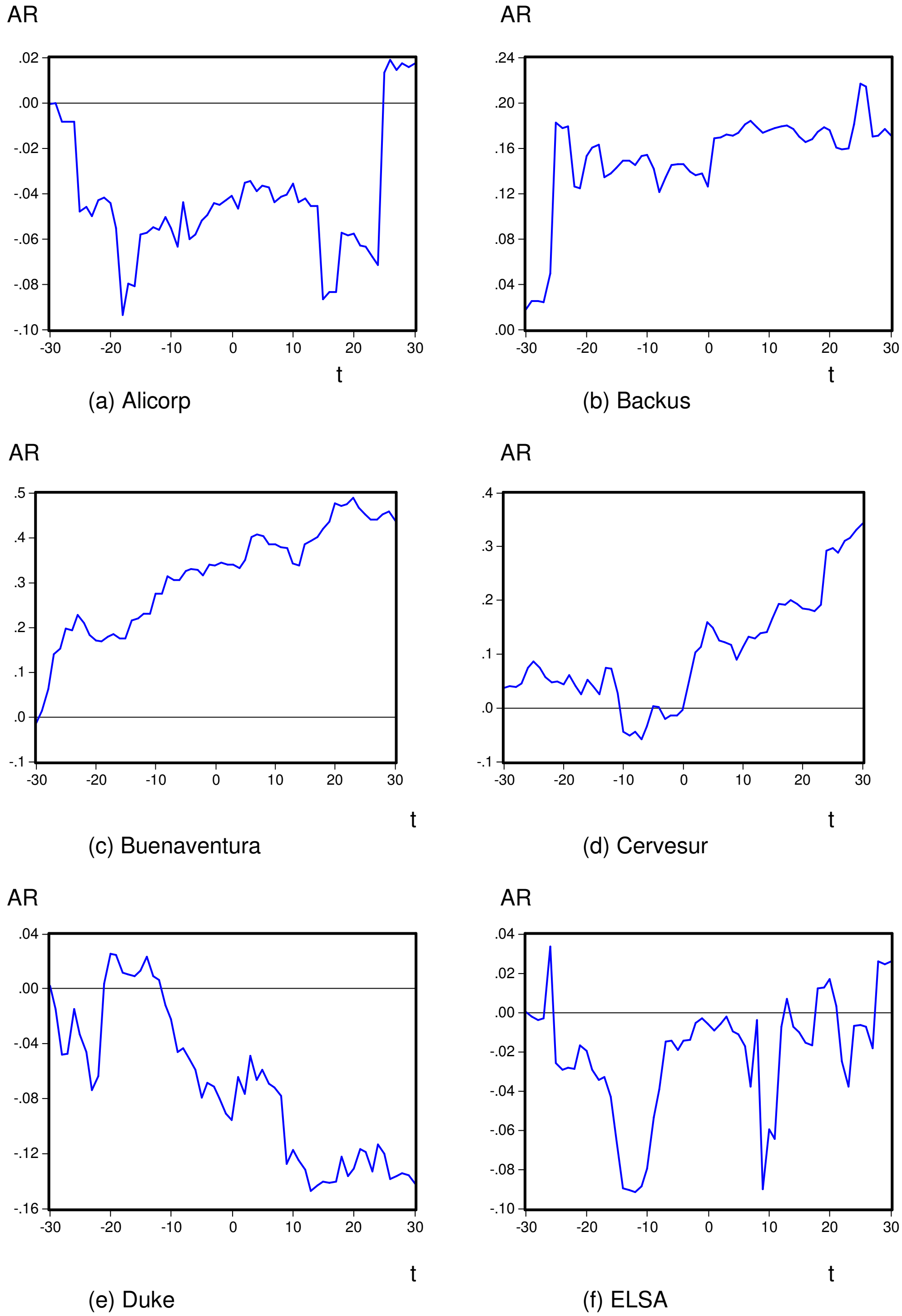
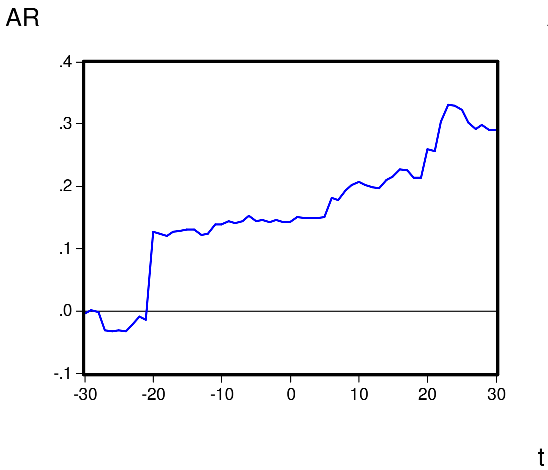
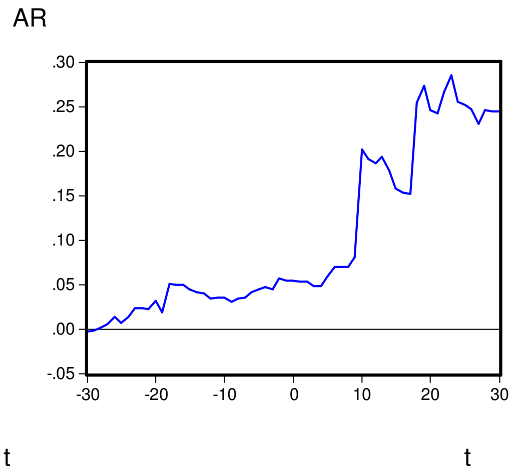


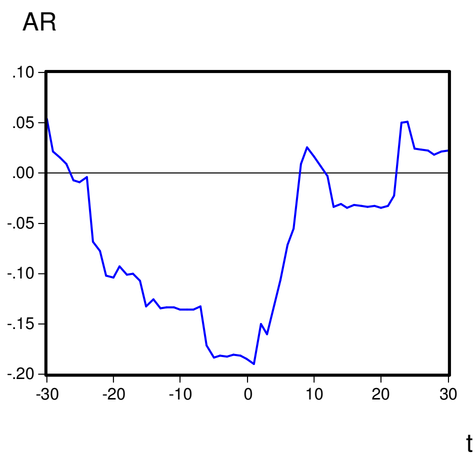
Figure 7-2
Cumulative abnormal returns by firm
Market-adjusted model



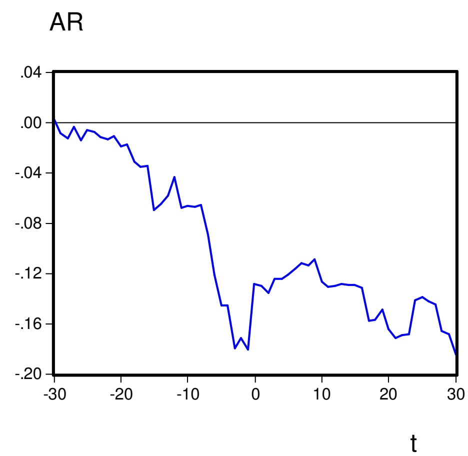
(g) Goodyear



(h) Malteria Lima



(i) Milpo



(j) Volcan

Figure 8-1
Cumulative abnormal returns by firm
Market Model - GARCH

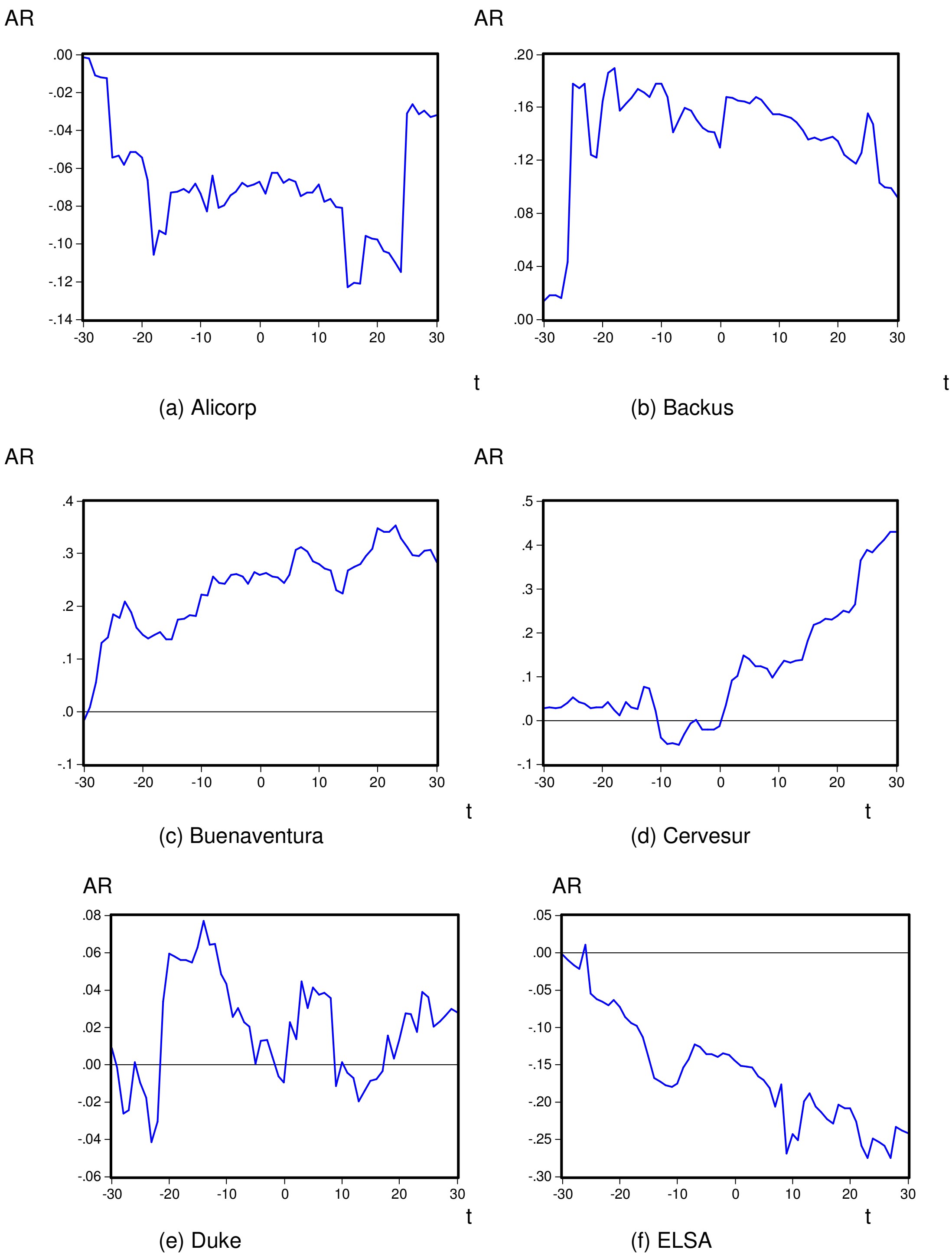
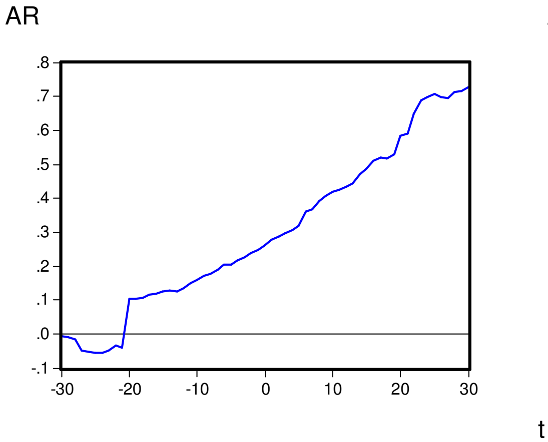
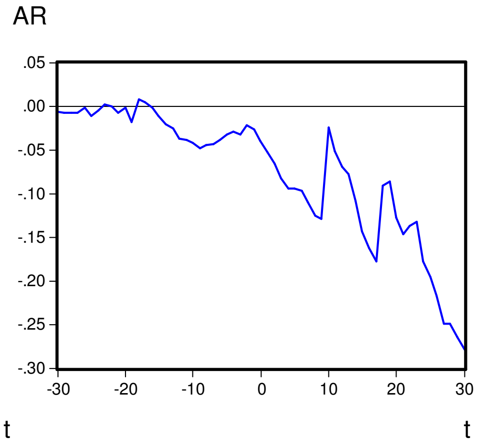


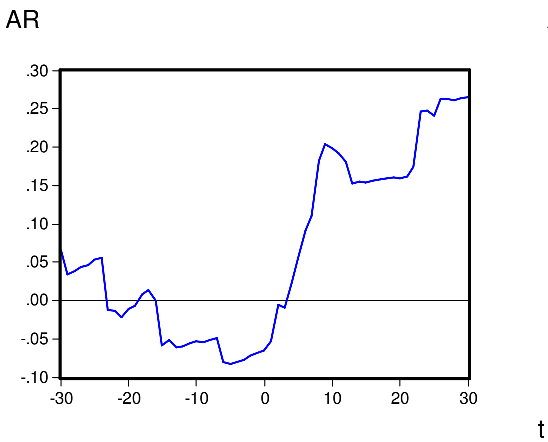
Figure 8-2
Cumulative abnormal returns by firm
Market Model - GARCH



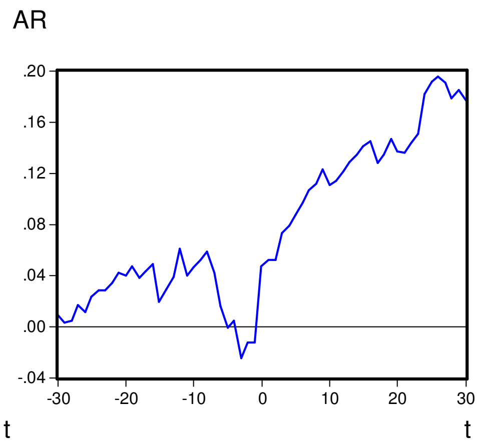
(g) Goodyear



(h) Malteria Lima



(i) Milpo



(j) Volcan

Figure 9-1
Cumulative abnormal returns by firm
Market Model – GARCH – Downside beta

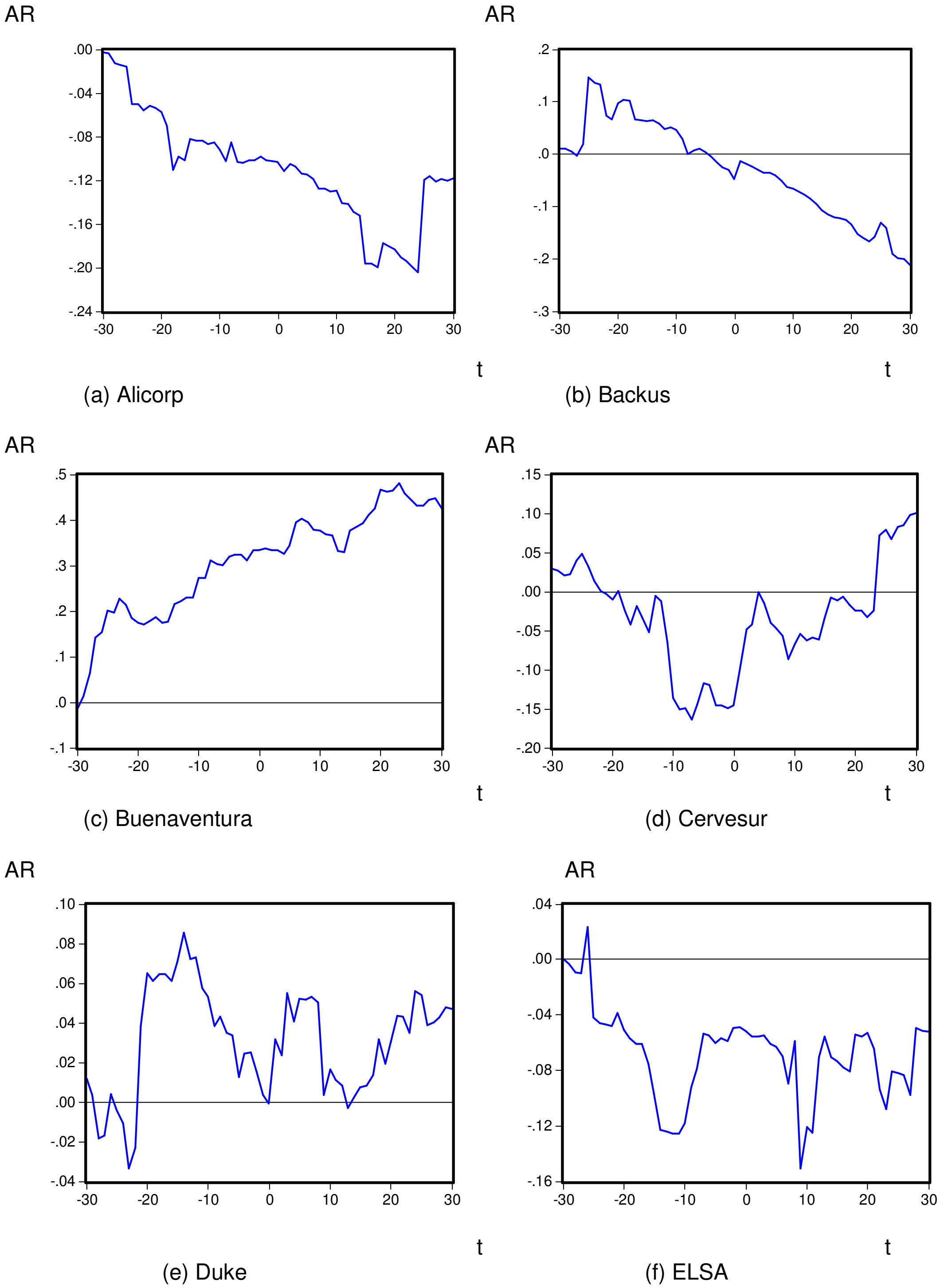
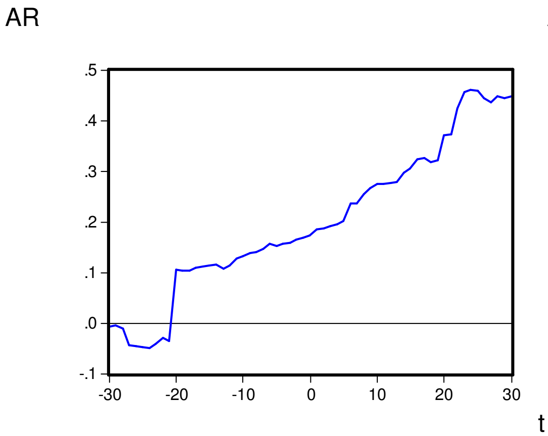
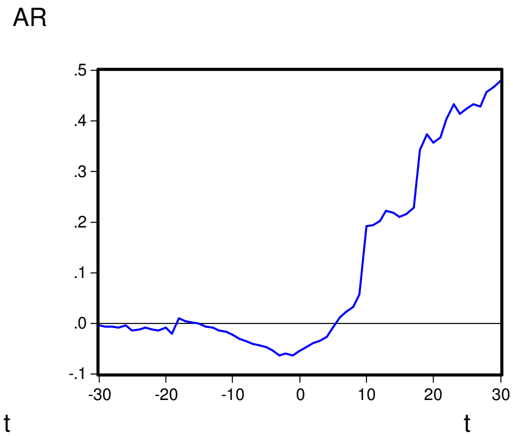


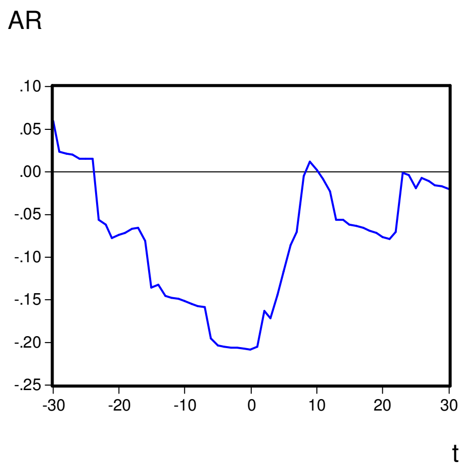
Figure 9-2
Cumulative abnormal returns by firm
Market Model – GARCH – Downside beta



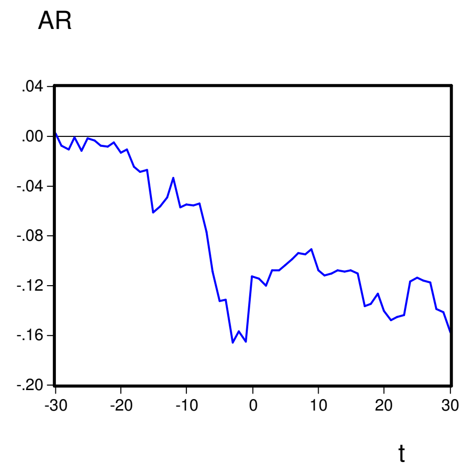
(g) Goodyear



(h) Malteria Lima

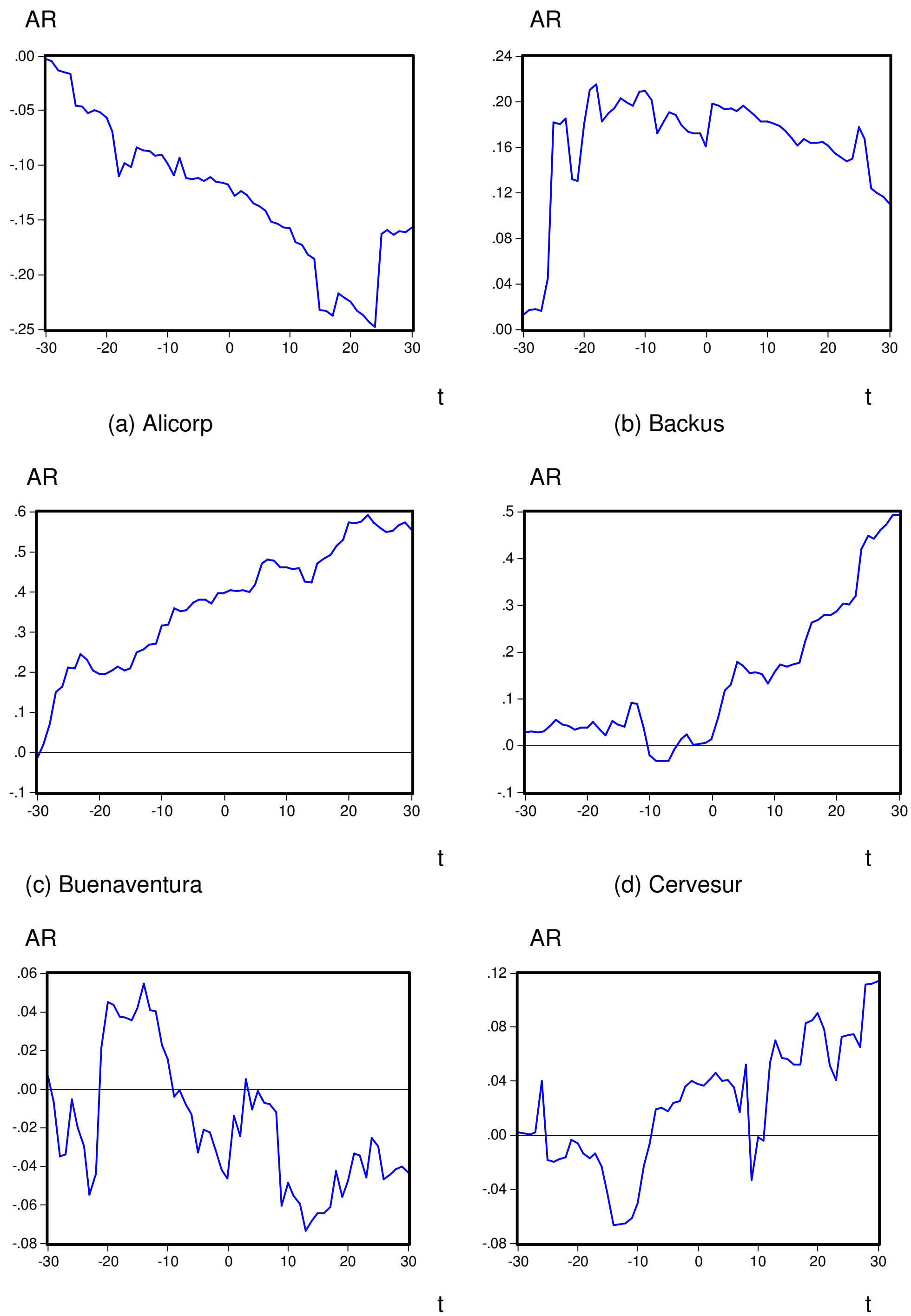


(i) Milpo



(j) Volcan

Figure 10-1
Cumulative abnormal returns by firm
Market Model - Theil



(a) Alicorp

(b) Backus

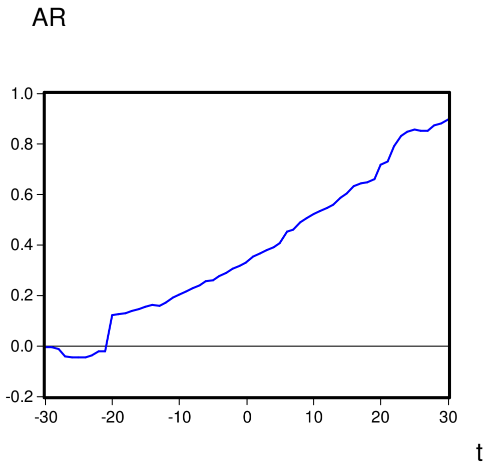
(c) Buenaventura

(d) Cervesur

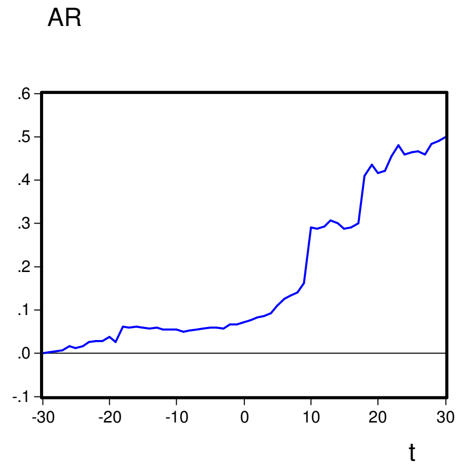
(e) Duke

(f) ELSA

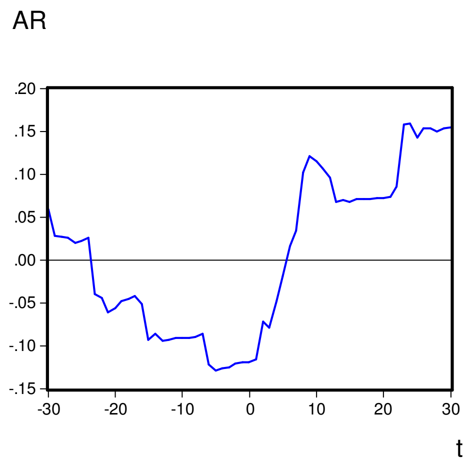
Figure 10-2
Cumulative abnormal returns by firm
Market Model - Theil



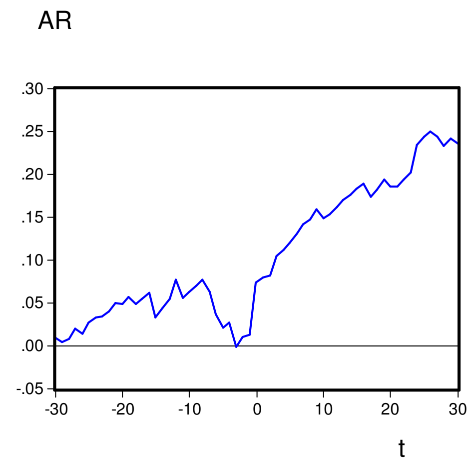
(g) Goodyear



(h) Malteria Lima

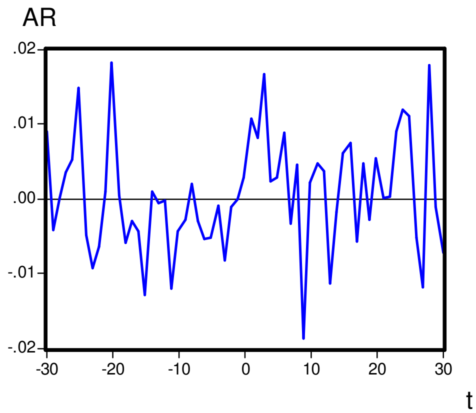


(i) Milpo

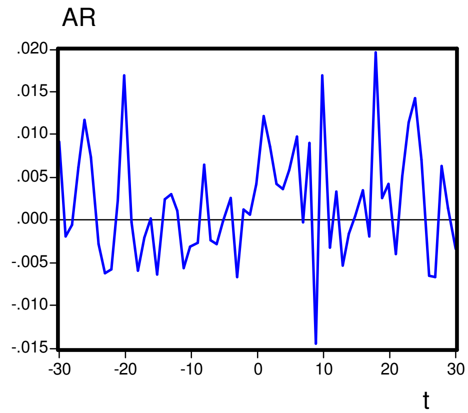


(j) Volcan

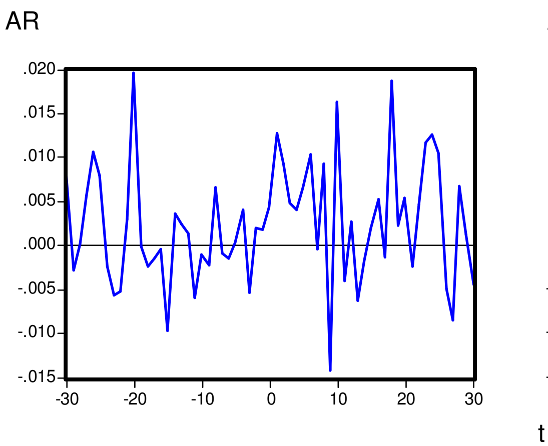
Figure 11
Average abnormal returns
Sample of 10 firms



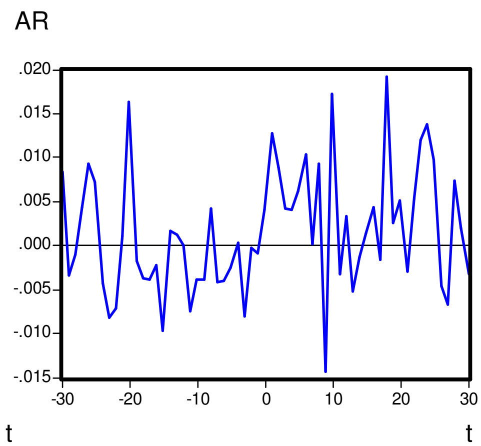
(a) Constant-mean return model



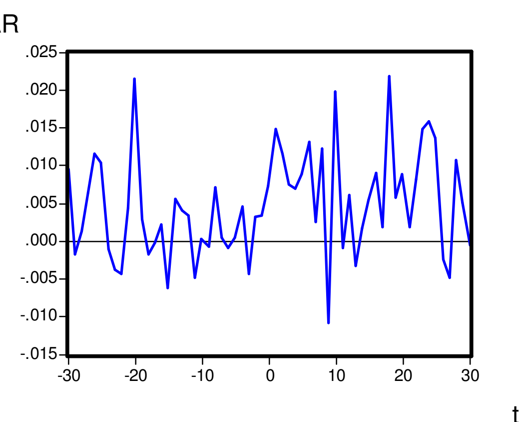
(b) Market-adjusted model



(c) Market Model – GARCH

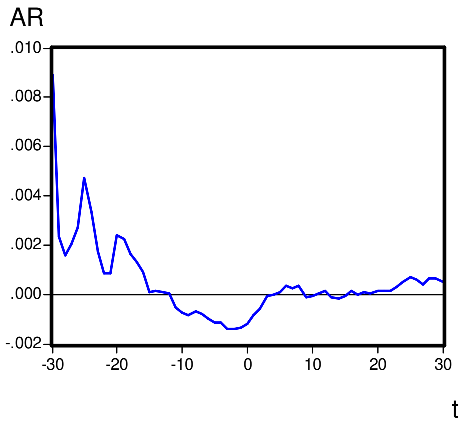


(d) Market Model – GARCH – Downside beta

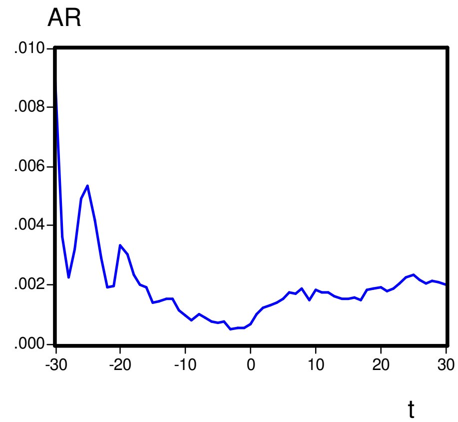


(e) Market Model – Theil

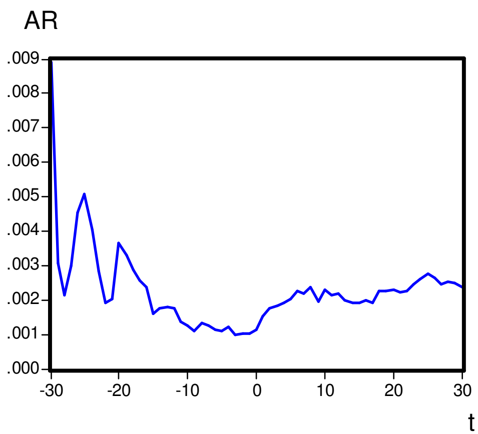
Figure 12
Average cumulative abnormal returns
Sample of 10 firms



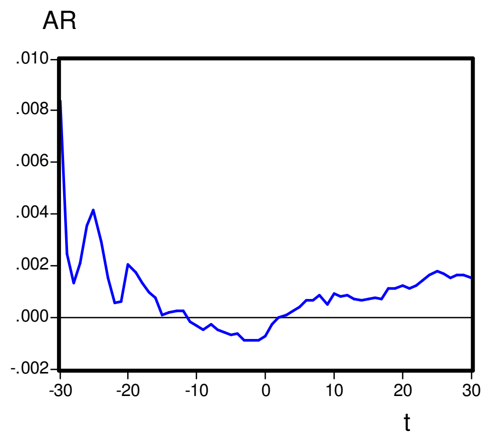
(a) Constant-mean return model



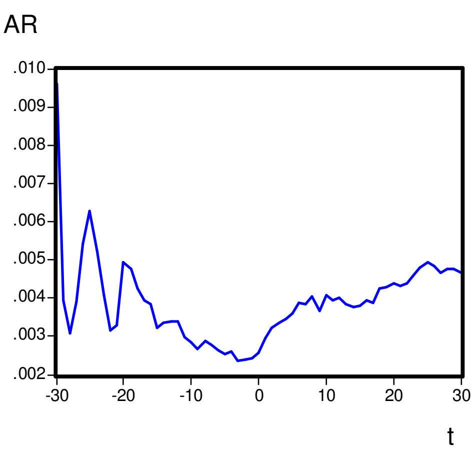
(b) Market-adjusted model



(c) Market Model – GARCH



(d) Market Model – GARCH – Downside beta



(e) Market Model – Theil

Table 5-A
Statistical significance of average cumulative abnormal returns (CAAR)
Sample of 10

	Constant-mean return model					**Market-adjusted model**				
(t1,t2)	CAAR	J1	J2	J3	J4	CAAR	J1	J2	J3	J4
(-30,30)	0.00052	0.07612	0.00477	0	-0.59131	0.00204	0.31489	0.25001	0	0.84762
(-25,25)	0.00051	0.07418	0.02439	0	-0.82917	0.00213	0.3198	0.27005	-0.79057	0.83928
(-20,20)	-0.00004	-0.0066	-0.12018	-0.6455	-0.8667	0.00194	0.32117	0.24463	-0.79057	0.26359
(-15,15)	-0.00053	-0.0845	-0.27116	-0.6455	-1.03804	0.00136	0.23408	0.2415	-0.79057	0.1089
(-10,10)	0.00037	0.0611	-0.15748	-0.6455	-0.44551	0.00263	0.43177	0.45861	0	0.63461
(-5,5)	0.00276	0.47758	-0.33067	-1.29099*	-0.15752	0.00363	0.81285	0.82175	0.79057	2.14550**
(0,0)	0.00282	0.02817	0.02803	-2.58199***	-0.97426	0.00417	0.04168	0.04148	-3.16228***	-0.70105
(-1,1)	0.00671	1.45420*	-1.05256	1.29099*	-0.34715	0.00844	1.77601**	-1.00664	-1.58114*	-1.21655
(-30,-1)	-0.00139	-0.21201	-0.42241	-1.93649**	-1.1763	0.00055	0.08748	-0.00507	-3.16228***	-0.38354
(-25,-1)	-0.00224	-0.34048	-0.50009	-1.93649**	-1.49525*	-0.00036	-0.05659	-0.1546	-3.16228***	-0.57496
(-20,-1)	-0.00256	-0.44379	-0.65537	-1.93649**	-1.25438	-0.00018	-0.0334	-0.15456	-2.37171***	0.61312
(-15,-1)	-0.00387	-0.82388	-0.97207	-3.22749***	-0.36908	-0.00089	-0.19669	-0.15642	-2.37171***	0.80397
(-10,-1)	-0.00326	-0.83163	-1.01571	-2.58199***	-1.26562	-0.00079	-0.18335	-0.07641	-2.37171***	-0.88532
(-5,-1)	-0.00394	-1.34898*	-1.64583**	-2.58199***	-1.27836	-0.00058	-0.1883	0.09773	-2.37171***	-0.29566
(1,30)	0.00237	0.33965	0.23571	-1.29099*	-0.72516	0.00352	0.54429	0.46442	0	1.113
(1,25)	0.00318	0.46499	0.45341	1.29099*	-0.2434	0.00462	0.67858	0.66383	-0.79057	1.40724*
(1,20)	0.00233	0.34825	0.23874	0	-0.71676	0.00405	0.62691	0.57475	-0.79057	-0.40974
(1,15)	0.00252	0.35037	0.20678	-0.6455	-0.58227	0.0035	0.53309	0.5289	-1.58114*	-0.53048
(1,10)	0.00378	0.53004	0.09533	0	0.81956	0.00616	0.88822	0.99298	0	0.97692
(1,5)	0.01014	1.53580*	-1.25332	0	2.06576**	0.00863	1.93780**	1.54349*	0.79057	1.78389**

	Market Model - GARCH					**Market Model - GARCH - Downside beta**				
(t1,t2)	CAAR	J1	J2	J3	J4	CAAR	J1	J2	J3	J4
(-30,30)	0.00242	0.37208	0.35985	1.93649**	0.98162	0.00157	0.23963	0.18503	4.21637***	0.80281
(-25,25)	0.00264	0.39622	0.39588	1.93649**	1.13268	0.00163	0.24218	0.20441	4.21637***	0.94243
(-20,20)	0.00243	0.40093	0.35679	1.29099*	0.95335	0.00138	0.22307	0.05379	3.16228***	0.97844
(-15,15)	0.00173	0.29518	0.53287	0.6455	0.52079	0.00069	0.11531	0.09951	4.21637***	0.61049
(-10,10)	0.00337	0.57131	0.84678	1.29099*	0.98764	0.00201	0.32273	0.30559	4.21637***	1.1326
(-5,5)	0.00449	1.00813	1.23167	2.58199***	1.1392	0.00288	0.64438	0.73774	6.32456***	2.03434**
(0,0)	0.00438	0.04382	0.04362	0.6455	-0.62969	0.00413	0.04127	0.04107	3.16228***	-0.70683
(-1,1)	0.00951	2.05229**	1.39028*	1.93649**	0.83928	0.008	1.68254**	1.38825*	7.37865***	-0.58575
(-30,-1)	0.00108	0.16894	0.03298	-0.6455	-0.23742	-0.00091	-0.14419	-0.31512	2.10819**	0.22234
(-25,-1)	0.00036	0.05626	-0.07948	-0.6455	-0.75773	-0.00184	-0.2907	-0.44519	1.05409	-0.55321
(-20,-1)	0.00057	0.10459	-0.07265	-0.6455	-0.24181	-0.00171	-0.31394	-0.50257	1.05409	0.22807
(-15,-1)	-0.00031	-0.06732	0.25769	-0.6455	0.43201	-0.00267	-0.58716	-0.7952	2.10819**	0.58987
(-10,-1)	0.00042	0.10601	0.87953	0	-0.72524	-0.00255	-0.61681	-0.71535	2.10819**	-1.14292
(-5,-1)	0.00072	0.24638	0.86278	1.29099*	-0.19847	-0.00284	-0.94705	-1.82080**	3.16228***	-1.24463
(1,30)	0.00377	0.59225	0.74345	1.93649**	1.52639*	0.00401	0.62129	0.47949	5.27046***	1.89841**
(1,25)	0.00497	0.74177	0.97077	2.58199***	1.90885**	0.00507	0.74576	0.64373	5.27046***	1.90257**
(1,20)	0.00432	0.67311	0.93348	1.93649**	1.69296**	0.0044	0.67708	0.45517	5.27046***	1.48340*
(1,15)	0.0037	0.56717	1.06383	1.93649**	1.16993	0.00385	0.58198	0.49788	6.32456***	2.01595**
(1,10)	0.00658	0.97623	1.49646*	2.58199***	1.94415**	0.00655	0.94035	0.84216	6.32456***	2.12307**
(1,5)	0.00942	2.23065**	1.90792**	1.93649**	1.33957*	0.00901	2.10924**	2.20762**	7.37865***	2.14475**

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

Table 5-B
Statistical significance of average cumulative abnormal returns (CAAR)
Sample of 10

Market Model - Theil					
(t1,t2)	CAAR	J1	J2	J3	J4
(-30,30)	0.00475	0.73076	0.68066	0	0.79185
(-25,25)	0.005	0.74728	0.71156	0	0.9387
(-20,20)	0.00475	0.77966	0.63528	0	0.9369
(-15,15)	0.00394	0.67612	0.86388	-0.79057	0.88051
(-10,10)	0.00536	0.89329	1.08222	-0.79057	1.42592*
(-5,5)	0.00642	1.46258*	2.27327**	0.79057	2.30930**
(0,0)	0.00723	0.0723	0.07196	-1.58114*	-0.28328
(-1,1)	0.01267	2.77249***	4.55076***	0.79057	0.29018
(-30,-1)	0.00251	0.39685	0.29925	-0.79057	0.63513
(-25,-1)	0.0019	0.30087	0.19375	-3.16228***	0.44766
(-20,-1)	0.0021	0.388	0.2305	-2.37171***	1.15609
(-15,-1)	0.0011	0.24683	0.66119	-3.16228***	1.01344
(-10,-1)	0.00149	0.37313	1.37290*	-3.16228***	-0.54243
(-5,-1)	0.0018	0.62346	1.10956	-1.58114*	0.11355
(1,30)	0.00708	1.10634	1.14294	0	1.17176
(1,25)	0.00821	1.2193	1.34858*	0.79057	1.48516*
(1,20)	0.00752	1.16875	1.25802	0	1.42488*
(1,15)	0.00683	1.04526	1.43673*	0	0.85265
(1,10)	0.00963	1.41205*	1.62031*	-0.79057	2.43328***
(1,5)	0.01244	2.93841***	4.07232***	0.79057	2.20415**

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