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Cross-listing Premium or Market Timing

Moustafa M. Abu El Fadl
Old Dominion University

CROSS-LISTING PREMIUM OR MARKET TIMING

By

Moustafa M. Abu El Fadl
B.S.C. in Business Administration, November 1995, Helwan University
Graduate Diploma in Investment Finance, June 1998, Ain Shams University
M.B.A., May 2003, University of Arizona
M.A. in Economics, August 2009, Old Dominion University
C.F.A., September 2009, CFA Institute

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Approved by:

(Director)

(Member)

(Member)

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ABSTRACT

Moustafa M. Abu El Fadl
OldDominionUniversity, 2011
Director: Dr. Mohammed Najand

Previous research documented that soon after companies cross-list; they achieve significant negative post-listing abnormal returns (the post-listing anomaly). The evidence presented in this study shows that companies cross-list based on either a market-timing consideration or a genuine performance consideration. The host market condition is significant in explaining both the sign and the significance of post-listing abnormal returns. On the one hand, the evidence reveals, companies that cross-list in a host market while that host market is "positive" and achieve a significant negative post-listing abnormal returns, those companies time the market, and the post-listing anomaly is explained in the context of market timing. On the other hand, if companies cross-list in a host market while that host market is "negative" and achieve a positive post-listing abnormal return whether it is significant or not, means those companies did not time the market, which also indicates that the post-listing anomaly does not exist.

Event studies are based on grouping companies by certain characteristics, such as the choice of benchmarks affects the method of forming portfolios of different companies, which in turn affects both the sign and the significance of the post-listing abnormal returns. The sample evidence shows for some of the different characteristic index benchmarks used, different estimation procedures changed the sign and the significance of the post-listing abnormal returns. For the entire different market index benchmarks used, however, different estimation procedures did not change the sign or the significance of the post-listing abnormal returns. The GARCH (generalized autoregressive conditional heteroscedasticity) estimation procedure is a better fit when using daily returns to estimate abnormal returns, and the characteristic index is a better fit when forming portfolios of companies based on certain characteristics.

Discretionary accruals research reports if companies have a high degree of discretionary accruals, then those companies engage in earnings management. I built a dummy variable *DTIMERS* that takes the value of 1 if the companies time the market and 0 if they do not. I ran multiple regression models where *Absolute Discretionary Accrual* is the dependent variable, with *DTIMERS* as an independent variable along with other control variables. I used a wide variety of both parametric and non-parametric tests, and diagnostic regression analyses adjusting for heteroscedasticity and autocorrelation. The evidence shows the companies that time the market engage in earnings management and that may explain why those companies in the post-listing period achieve significant negative abnormal returns.

This study contributes to the literature by highlighting the relationship between the cross-listing decision, host market condition, post-listing abnormal return, and earnings management. Researchers of cross-listing must take into consideration all those factors, investors ought not buy shares of cross-listing companies without conducting due diligence, and financial analysts should not recommend buying a firm's stock that is cross-listed unless they have examined the timing of cross-listing and signs of earning.

This study leaves open the possibility for further research to study such questions as does cross-listing create value for non-market timers, and does the market generally overreact to cross-listing, regardless of whether or not the companies time the market.

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CHAPTER 1
WHY DO COMPANIES CROSS-LIST?

1.1 INTRODUCTION

Cross-listing can be seen as a viable way for business to join the global economy. In addition, it can be seen as a way for firms to internationalize their operations without moving them to a different country or overseas. Foerster and Karolyi (1999), and Karolyi (2003) point out that the pace of globalization in capital markets has accelerated in the past two decades. Overseas firms choose either to issue new stocks on a foreign exchange or, if they are already listed on a foreign exchange, cross-list their stock on a foreign exchange market. Of note, most firms that cross-list, do so on U.S. exchanges. Cross-listings are important catalysts for cross-border capital flows and capital flows are positively linked to financial market liberalizations, which, in turn, are associated with higher real per capita growth (Bekaert et al., 2001; Bekaert et al., 2002). The following figure supports those ideas.

$< Insert\ Figure\ 1 >$

According to *Coordinated Portfolio Investment Survey* cross-border holdings of portfolio investment reached US$19.05 trillion in 238 economies in 2003. Of the total cross-border holdings reflected in the survey, US$6.9 trillion was in equity securities and US$12.15 trillion in debt securities. Data also show that an increase in cross-border holdings of portfolio investment reached a maximum of US$39 trillion in 2007 and then declined in 2008 to about US$30 trillion. Additionally, the data show the ratio of total investments in the United States with respect to investment from that country had been decreasing from 2003 to 2007, but had turned around in 2008, with an increase in that ratio.

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$< Insert\ Figure\ 3 >$

In this chapter, I was motivated to answer a question first asked in Doidge et al. (2004): do companies that cross-list achieve a cross-listing premium simply because the host market is "up"? In attempting to answer that question, a broader question presented itself. Why do companies cross-list? Exhaustive research has been conducting concerning the reasons for cross-listing. One line of research sees cross-listing as the internationalization of companies stocks that can leads to better investment decisions. According to Stapleton and Subrahmanyam (1977), Alexander et al. (1987), Eun and Janakiramanan (1986), and Errunza and Losq (1985), cross-listing will lead to higher equilibrium market prices and lower expected returns, especially if the markets are segmented. Additionally, Hargis and Mei (2000) find companies want to cross-list because they believe that cross-listing will increase the company's value and enhance the liquidity of the underlying stock. The revaluation arises from eliminating the risk premium that represents compensation to local investors for their inability to diversify their risks globally.

From the microstructure perspective, companies choose to cross-list their shares overseas for liquidity; while that seems legitimate, scholars have agreed that the competition that ensues from multiple markets' trading the shares does affect how information is incorporated into prices. This is true for either domestic or foreign markets that will attract most of the order flow. No consensus is found among scholars as to why and how the order flow gravitates to one market or another, but one thing is true from those companies that do cross-list and seek out investment banking advisors to sell their stock publicly to clients: they achieve lower returns compared with those companies that raise capital only in their home market.

Managers typically state that they cross-list their companies stock to gain access to foreign capital markets as well as to lower the company cost of capital, increase their ability to raise equity, increase their shareholder base, make their stock more liquid, and add visibility, exposure, and prestige (Mittoo, 1992a, 1992b; Fanto and Karmel, 1997). Merton (1987) formally develops an investor recognition hypothesis, based on his model of capital equilibrium with incomplete information and suggests that increases in measures of investor recognition should also be associated with reductions in companies' costs of capital. Numerous studies, such as those of Alexander et al. (1988), Karolyi et al. (1998), Lau et al. (1994), and Miller (1999) agree with Merton's suggestion. However, other studies by McConnell (1987), McConnell (1987), and Dharan and Ikenberry (1995) found out that although the number of shareholders increases after cross-listing, cross-listing is associated with lower returns. Most of the empirical studies on international listings addressed the share price reactions around a company's listing decision. Studies by Lee (1991), Torabzadeh et al. (1992), Varela and Lee (1993a, b), and Lau et al. (1994) found either slightly positive or neutral market reactions occurred in the listing month.

This chapter aims to clarify the relationship between cross-listing decisions and post-listing returns. It aims to expand the domain of cross-listing by including a broader view that allows for analyzing the motives of cross-listing decisions. I opted for an event study using an econometric approach grounded in theory that includes 32 companies from eight different countries. The study begins with a review of the literature concerning cross-listing, the topics examined in terms of the reasons to cross-list, and attempts to answer why companies cross-list. While that question seems very basic, it is difficult to search the motives of companies, unless we go company by company and analyze each one in detail. That might seem a legitimate way to answer the question, but if I did, I will not be able to provide a coherent argument that applies to the generic question, because obviously each company is different. My methodology involved examining the connection between post-listing abnormal returns and the initial cross-listing decision. In the cross-listing literature,[1] the main theme that emerged is most companies achieve significant negative abnormal returns after they cross-list, referred to in the literature as the *post-listing anomaly*. One could stop there, but then that raises another question, why does such an anomaly exist, if it really does. Instead, if we want to answer the combined questions of why companies cross-list and why there is a "post-listing anomaly," then a connection between those two questions can be explored.

To find an answer, I developed a common factor between those two questions, which is "the host market condition." I used the market index return for the Dow Jones Industrial Average (DJIA), because all the companies in the study were compared with those listed in the DJIA. After establishing the common factor, then the analyses were developed around four hypotheses that mainly argue when companies cross-

[1] See the literature review.

list and achieve significant negative abnormal returns (confirming the anomaly), then those companies time the market only if the host market condition is a positive in the post-listing period. Of course, there are some variations to that, which I will explain in detail in Chapter 2 in sections 2.6 through 2.8.

The study uses a wide variety of parametric and non-parametric tests to test each of the hypotheses, and the reason to do so is the distribution properties of the daily stock returns, as they do not follow the normal distribution characteristics. I also examine in detail those distributional properties. Then the study uses the Fama-French procedure to examine the possibility of whether the DJIA is the best index to use. Moreover, Fama-French (1993, 1995) control for size and book-to-market ratio (BTM) factors that affect the cross-sectional of stock returns.

This study contributes to the literature in several ways. First, it proposes an attempt to investigate the motives of cross-listing companies and explain the "post-listing anomaly." Second, to mitigate the impact of biases resulting from the skewness of the distribution on measuring post-listing abnormal returns, the choice of different reference portfolios and an appropriate use of a bootstrapping methodology and skewness-adjusted test statistic suggested by Lyon, Barber, and Tsai (1999) are used. Moreover, the study goes beyond documenting abnormal returns behavior and relates that behavior to market-timing decisions by managers.

1.2 LITERATURE REVIEW

It is well-established in the literature that international cross-listings have significant and positive valuation effects. Merton (1987) developed a model based on capital asset pricing models (CAPM) but relaxed the assumption of equal information across investors. As such, expected returns increase with systematic risk, a company's specific risk, and relative market value, and decrease with the relative size of the company's investor base—characterized by the degree of investor recognition. According to Merton (1987), ceteris paribus, an increase in the size of a company's investor base will lower investors expected return and increase the market value of the company's shares.

Pagano et al. (2002) and Leuz et al. (2005), find that companies listing abroad to have better access to foreign markets. Liquidity effects come from the reduction of trading costs through listing in a more "liquid" exchange and through inter-market competition as well as from order flow migration (Domowitz et al., 1998. P2015).

One of the reasons change occurs in a company's average return when it chooses to cross-list is a result of capital markets being either completely or mildly segmented (Domowitz et al., 1997; Miller, 1999). According to Alexander et al. (1988), segmentation of capital markets produces incentives for companies to adopt financial policies that can effectively reduce any associated negative effects. In addition, according to Stapleton and Subrahmanyam (1977), in completely integrated capital markets, dual-listing of a company's stock on a foreign capital market would not be expected to significantly affect its price. If, however, capital markets are either completely or mildly segmented, then such a dual-listing would be expected to have a significant effect on the company's stock price. Previous research conducted by Stapleton and Subrahmanyam (1977), Alexander et al. (1987), and Errunza and Losq (1985) suggests that international listing will lead to a reduction in the expected return on the security if capital markets are either completely or mildly segmented. Bris et al. (2007) find support for the market-segmentation hypothesis.

Stulz (1999) has challenged these established ideas of integrated or segmented markets, who points out that even companies from countries that are substantially integrated into world markets enjoy cross-listing abnormal returns. Domowitz et al. (1997) show that liquidity in the home market decreases after an American depository receipt (ADR)-program. Recent papers have put forth new explanations for the value effects of dual listings. The bonding hypothesis was empirically studied in Doidge (2004 a,b) and Doidge et al. (2004), and it is based on the work of Coffee (1999, 2002), Stulz (1999), and Reese and Weisbach (2002). The bonding hypothesis posits stipulates that cross-listing on a U.S. exchange enhances investor protection. In a similar vein, Cantale (1996), Fuerst (1998), and Moel (1999), characterize signaling equilibrium whereby companies cross-list in markets with high disclosure standards to convey that they are high-value companies. Miller (1999) conducts an event study concentrating on the 80-day period around the ADR-initiating announcement dates of 183 companies between 1985 and 1995, and finds a positive 1.15% average abnormal return. He also finds higher abnormal returns for companies in emerging markets (1.54%) and that these abnormal returns were higher for exchange listings (2.63%). Foerster and Karolyi (1998) concluded that market segmentation could not explain these results and relate the findings with management's strategic market-timing decisions

Doidge, Karolyi, and Stulz (2004) argue that cross-listing helps controlling shareholders' commitment to limit their expropriation by minority shareholders. Doidge, Karolyi, and Stulz (2004) predict that cross-listing companies have higher growth opportunities than their peers that do not cross-list. Doidge, Karolyi, and Stulz (2004) show that foreign companies listed in the United States have a Tobin's-Q ratio that is 16.5% higher than the Q ratio of companies from the same country that do not list in the United States.

Managerial decisions rely in part on the information conveyed by stock prices (Jegadeesh et al., 1993; Markovitch et al., 2005; Bakke and Whited, 2007; Chen et al., 2007). Foucault and Menkveld (2008) show those cross-listing enables companies to obtain information from the stock market about the value of their companies' growth opportunities and those companies with perceived greater growth opportunities will list at higher premium than the ones who are not perceived as such. Karolyi's (2006), model describes another mechanism through which a cross-listing could affect a company value, which he called the information channel. Thus, such findings imply the existence of a cross-listing premium. This implication is important as several researchers document such a premium for companies cross-listed in the United States (e.g., Doidge et al.,2004; King and Segal, 2006; Gozzi et al.,2008). They also show that the cross-listing premium persists when they control for the size of growth opportunities. A cross-listed company exploits its growth opportunities more efficiently, as its manager reaps greater benefit from a more informative stock price. This implication is also consistent with the empirical findings in Doidge et al., (2004), who argue that the cross-listing premium reflects more stringent governance regulations in the United States. Their theory shows that this premium could also stem from an improvement in stock price informativeness.

Karolyi and Stulz, (2002) argue that cross-listing lower the cost of capital for companies as it makes their shares more accessible to non-resident investors . Coffee (1999, 2002), Stulz (1999), and Reese and Weisbach (2002) argue that the empirical support for this global risk-sharing hypothesis relies on event study tests showing that the announcement of a U.S. listing accompanied by a significant abnormal return is higher for companies from emerging markets and for listings on the major exchanges.

Stulz (1999) and Coffee (1999, 2002) argue that by cross-listing, companies are able to enhance investor protection by bonding to the U.S. legal and regulatory regime, and, as a result, reduce agency costs. Reese and Weisbach (2002), Doidge (2004, a, b), and Desai et al. (2004) provide evidence broadly consistent with the legal bonding hypothesis. Others however, have questioned whether cross-listing does in fact result in legal bonding. La Porta et al. (2000) and Licht (2003) argue that instead of bonding, the insiders of cross-listed companies are more likely to take advantage of the relatively lax U.S. enforcement of the laws. Burns et al. (2006) find that cross-listing in the United States does enhance the investor protection of the cross-listed company. That is, U.S. investors take cross-listing by foreign companies as a credible signal that they intend to respect shareholders rights.

Bris (2007)explores the differential effects of cross-listing on prices and separates the different sources of the benefits of cross-listing. They find that the data support the market-segmentation hypothesis. They also find evidence consistent with the bonding hypothesis: they document a voting premium before the listing, and this premium is significantly reduced after the listing. Ammer et al. (2005) provides little support for the bonding hypothesis.

Empirically, it is very difficult to disentangle these hypotheses. Miller (1999) found that some result is consistent with market segmentation, and also consistent with the signaling, bonding and liquidity hypothesis.

1.3 HYPOTHESES DEVELOPMENT

One of the most important anomalies in the financial markets is that stock prices appear to rise immediately before listing, but they decline after listing and continue to decline for some companies some time. Companies' reasons for cross-listing are based on such criteria as an increase of their prestige, stock visibility, the effect of signaling, and the improvement of liquidity and managers preferences. Companies are unlikely to use the listing mechanism for generating signals, because of listing costs and the risk of being delisted.

Merjos (1963, 1967) investigated the price behavior of newly listed stocks three months before listing and one month after listing. She found that the sample outperformed the market in the three month period before listing, but underperformed the market during the one month period after listing. She concluded that the anticipation of listing was the primary factor in the pre-listing price performance, but could determine no explanation for the post-listing performance. Furst (1970) adapted a multiple regression model to analyze the stock prices of companies that changed trading locations and found that the market price was not significantly greater after listing. So listing per se does not significantly affect the market prices of common stock, when other factors are considered. Goulet (1974) suggested that an increase in the supply of shares outstanding would depress prices in the short run. He attributed the post-listing anomaly as the change in the supply of shares. Grammatikos and Papaioannou (1986) found negative abnormal returns even after excluding the excess supply; therefore, the explanations for post-listing anomaly were unsatisfactory. Furst (1970) and Van Home (1970) pointed out that risk factors may be an explanation, but Reints and Vandenberg (1975) argued that in an efficient capital market, the act of listing should not affect a company's systematic risk level, and their study employing the Chow test found no significant change in the stock's systematic risk after listing. Subsequently, Fabozzi and Hershkoff (1979) confirmed those results.

Ying et al. (1977) employed the Fama-MacBeth procedure and found a substantial increase in pre-listing price, with, however, only a modest decline in post-listing. Further, such a decline in post-listing cannot offset the substantial increase in the pre-listing price, and they determined that listing offers value. Another possible explanation for significantly negative returns in the post-listing period is that investors initially overreacted to the news of listing. Sanger and McConnell (1986) investigated a comprehensive sample of 319 over-the-counter (OTC) stocks that listed on the NYSE from 1966 through 1977, and regardless of methodology used, they documented that stocks, on average, earn positive abnormal returns before listing and negative abnormal returns over the four-to-six-week period immediately following listing. Grammatikos and Papaioannou (1986) suggested that listing provides an informational value, because independent evaluation and approval by exchange may signal management confidence in the company. They cited that the signaling value of listing may differ among companies. They attributed the price gains accompanying cross-listing to a positive signaling value, but only for companies with low or volatile earnings performance before listing. Stocks with high-informational value (those with low-earning performance) exhibit a significant positive price reaction during the pre-listing period, but negative price reaction during the post-listing period. Stocks for which listing conveys low-informational value (those with high-earning performance) do not exhibit any significant market reaction.

McConnell and Sanger (1987), using a sample of 2,486 stocks that listed on the NYSE from 1926 through 1982, found that the average raw return and market-adjusted return over the first full month following listing were –0.78% and –1.45%, respectively. Baker and Edelman (1990) document that the market responds more favorably during pre-listing for stocks with low versus high liquidity and that there is a significant difference of performance in favor of low liquidity stocks versus high liquidity stocks. Baker and Edelman (1990) report that companies with a wide bid-ask spread (low liquidity) and low performance (high signaling) before listing, on average, realize gains by listing and vice versa. However, the evidence does not support the anomalous post-listing market behavior. Edelman and Baker (1993) found support that stocks with low liquidity and high signaling outperform high liquidity and low signaling in the pre-listing period, and they do not experience a general pattern of negative post-listing abnormal returns. Hwang and Jayaraman (1993) investigated whether the negative post-listing anomaly is a worldwide phenomenon, and whether the differences in the market-making mechanism explain the anomaly. Although the abnormal returns for the full sample were significantly positive, these returns were primarily driven by initial public offerings (IPOs), which did not begin trading immediately following their listing. The post-listing returns pattern for the non-IPO companies was negative.

Dharan and Ikenberry (1995) hypothesized that managers time the market and documented significant negative abnormal returns for up to 36 months after listing; however, there were some questions about their methodology, as pointed out by Lyon (1997). Charitou et al. (2007) studied 64 Canadian companies for the period between 1997 and 2003 that were cross-listed in the United States and found that cross-listing companies CEOs have substantial holdings of vested options exhibiting positive announcements returns and negative post-announcement long-run returns. Schill et al. (2008) note "cross-listing "waves" occur in a given host market when it does relatively well, with respect to other competing host markets for overseas listings".

One could argue that cross-listings are a corporate decision, and Lee (2003) offers some preliminary support of this view. Research conducted by Leuz et al. (2003) and Lang et al. (2003b) suggests that, relative to U.S. companies, cross-listed companies report smoother earnings. Foerster and Karolyi (1993) analyze 53 Canadian stocks cross-listed in the United States between 1981 and 1990 and find a significant positive pre-listing abnormal return of 9.35%, a 1.97% positive abnormal return over the week of cross-listing, and a significant negative post-listing abnormal return of 9.7%. Ko et al. (1997) examine 24 Japanese companies listed on the U.S. stock exchanges between 1970 and 1989 and found insignificant positive pre-listing abnormal returns, and, again, insignificant negative post-listing abnormal returns starting on the day after cross-listing, which suggests that listing on the U.S. exchanges has no significant effect on the value of Japanese stocks.

For some time, no convincing explanation had been extended relative to the post-listing decline of the abnormal returns, although several hypotheses were offered to solve what is called the "post-listing anomaly" (Baker et al., 1994). One hypothesis argues that the decline in stock prices following cross-listing can be attributed to the increase in the shareholder base. For example, Forster and Karolyi (1999) link the post-listing decline in the cumulative average annual return (CAAR) to the increase in the shareholder base caused by the new capital raised by the cross-listed stocks. Another hypothesis attributes the post-listing decline to management's timing of the cross-listing to follow superior performance in the company's operations; most studies appear to support the latter hypothesis. Additionally, Dharan, and Ikenberry (1995) argue that companies are most likely to time their cross-listing application to follow their good performance. They show that a post-listing decline in stocks' returns is confined to small companies that time their cross-listing with their good performance, which leaves their stocks exposed to decline after cross-listing. On the other hand, they show that large companies show no evidence of a post-listing decline in their stocks' returns. Their findings also support Forester's and Karolyi's (1999) earlier finding that attributed the post-listing decline to company-specific factors.

Thus, it has been observed that the "post-listing anomaly" (significant negative post-listing abnormal returns) is well-documented in the literature and host market conditions affect the returns of companies' cross-listing in that market. Moreover, most companies' primary objective to be obtained from listing is to maximize shareholders' returns. Taken in that context, this study confirms previous research that there is a pre-listing run-up in price and, hence, an increase in pre-listing returns and confirms that on or around the cross-listing date, there are positive returns.

This study aims to answer why do companies cross-list in terms of the post-listing abnormal returns; hence. The starting set of hypotheses is whether the "post-listing anomaly" exists.

H_0: Post-listing anomaly exists

H_A: Post-listing anomaly does not exist

The first set of hypotheses examines the relationship between host market condition, post-listing anomaly, and market timing. It is important to note when I mention anomaly, I refer to the fact that post-listing CAAR is a negative, which confirms the established idea of the anomaly. In doing so, the logic was if the host market was a positive and yet post-listing CAAR was a negative, then the "post-listing anomaly exists." Because I am using the market index return as a proxy for the host market condition and the same index return is used in the market model, which in turn, is used to determine abnormal returns, as such, if the host market condition was a positive then I expect positive abnormal returns. Thus, if after cross-listing, we have negative abnormal returns, then it follows we have a "post-listing anomaly," and vice versa. In addition, it follows that if the host market was a negative, and the post-listing anomaly exists, then that explains why the CAAR is a negative, and it follows that companies cannot be timing the market, because the market is already down.

$H1_A$: Post-listing anomaly exists

$H1_B$: Host market condition explains the anomaly

$H1_C$: Companies do not time the market

The second set of hypotheses continues from the same perspective, but in this case, the host market condition is a positive and the CAAR is a negative. Then it follows the anomaly exists but cannot be explained by the market condition. Therefore, companies must be timing the market and market participants must have expected it, so after the companies cross-list, they achieve negative CAAR.

$H2_A$: Post-listing anomaly exists

$H2_B$: Host market condition cannot explain the anomaly

$H2_C$: Companies time the market

The third set of hypotheses are built on the findings of the second set of hypotheses, and acknowledge the fact that it is not always the situation whereby companies achieve negative CAAR after cross-listing, which in itself cast doubts on the "post-listing anomaly." Continuing along the same lines, if post-listing CAAR is a positive and the host market condition is a positive, this may explain why CAAR is a positive. However, we cannot know if the companies time the market or not, because one can argue that some companies did time the market while others can argue that we cannot determine with certainty that they did time the market. Thus, in that case, the analysis is inconclusive.

H3$_A$: Post-listing anomaly does not exist

H3$_B$: Host market condition is a positive

H3$_C$: Companies time the market (inconclusive)

The fourth and last set of hypotheses continue similarly that if post-listing CAAR is positive and the host market is a negative, then it follows that the post-listing anomaly does not exist and companies will not time a market when it is a negative.

H4$_A$: Post-listing anomaly does not exist

H4$_B$: Host market condition is a negative

H4$_C$: Companies do not time the market

1.4 RESEARCH METHOD

This study examines returns on a daily basis and as Fama (1991, p. 1607) notes: "The cleanest evidence on market efficiency comes from event studies, especially event studies on daily returns. When an information event can be dated precisely and the event has a large effect on prices, the way one abstracts from expected returns to measure abnormal daily returns is a second-order consideration."

Event studies seek to analyze the impact of a specified class of events on the prices of securities. The pioneering work on event study was conducted by Ball and Brown (1968) and Fama et al. (1969). The methodologies used in these studies have become standard techniques for testing the EMH. Although several modifications have been made to the original methodologies, their basic structure has remained unaltered. The effect of the arrival of new information on a company's return may be interpreted as a change in the moments of the company's return distribution over the event period. With standard event study methodology, the test focuses on the change in the mean of the company's return distribution.

To discover the event impact, I need a measure of abnormal return. First, I define daily returns as

$$R_t = \frac{p_{t+1} - p_t}{p_t} \quad (1)$$

where R_t is the daily security i return at time t, $p_{t+1}$is the closing price of security i at time $+1$, and $p_t$is the closing price of security i at time t.

I explored the basic statistical measures for variable R_t. Table 1 reports that the mean daily stock returns for my sample is 0.001496, with a standard deviation of 0.04323. Next, I examined the significance of the variable R_t, with a t-statistic of 6.9442 and p-value of <0.0001, which shows that that the mean daily stock returns is significantly different from 0.

$< Insert\ Table\ 1 >$

$< Insert\ Table\ 2 >$

Choosing daily returns offers advantages and disadvantages that depend on distributional properties. To examine the distributional properties of daily returns, I fitted it against a normal curve. I used a non-parametric kernel density estimation to obtain smooth density estimate, and superimposed kernel density estimates on a histogram to visualize these features using smoother data. Figure 4 shows the kernel estimate (the upper curve) fits the distribution better than the normal fitted curve.

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I also examined the goodness-of-fit daily returns against normal distribution based on Kolmogorov–Smirnov ($D = 0.13245$) with a p-value of (0.01), I reject the null hypothesis and conclude that daily returns are not normally distributed. The Cramer–von Mises and Anderson–Darling tests also result in a p-value less than 0.05, which confirms the conclusion that the data are not normally distributed.

$< Insert\ Table\ 3 >$

I also produced a series of probability plots that help us visualize the behavior of daily returns under different sets of assumptions. These probability plots superimpose the theoretical normal distribution reference line; if returns came from normal distribution, the points would tend to follow the superimposed distribution line. Figure 5 shows that, as expected, daily returns do not conform to the superimposed theoretical reference normal line.

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In order to examine the possibility of using log normal returns instead of returns to transform the data to normal distribution, the probability plot of Figure 6 shows the use of log normal distribution did not cause the distribution to conform to normal distribution. In addition, I tried various estimation of sigma (not shown here), which yielded the same results.

$< Insert\ Figure\ 6 >$

The daily stock return for an individual security exhibits substantial departure from normality that is not observed with monthly data. Fama (1976, p. 21) reports that "the evidence generally suggests that distributions of daily returns are fat-tailed relative to a normal distribution". Brown and Warner (1985) indicate that this also the case for excess returns based on daily data. However, this fact need not necessarily bias hypothesis test toward type I error. Brown and Warner, 1980, 1985) provide evidence that the t-test is an accurate test for the presence of abnormal performance, despite the non-normality of the distribution of daily residuals. Peterson et al. (1990) reports that tests using daily returns are more powerful than those using monthly returns, and the non-normality of stock returns has little impact upon properties of test statistics. Brown and Warner (1980) document that daily returns have smaller standard deviations than do monthly returns. The use of daily data thus enables the research to take advantage of prior information about the specific day of the month on which the event took place.

Implicit in the t-tests that are used to assess abnormal returns are a number of strong assumptions: for example, in order for the test statistics to be distributed t-student security returns must be normally distributed. If such an assumption is not met, then the sampling distribution of test statistics assumed for the hypothesis tests could differ from the actual distributions, and false inferences could result. If the distribution of the test statistic is incorrectly specified, then the null hypothesis, when true, could be rejected with some frequency other than that given buy the significance level of the test. Hence, I used non-parametric tests that make less restrictive assumptions than the t-test; these include: the *sign test* and the *Wilcoxon signed rank test* (Kaplan and Roll, 1972; Brown and Finn, 1977; Collins, 1979).

1.4.1 Abnormal Returns Estimation

Researchers have used a variety of return-generating process models in lieu of the market model. After extensive research, Brown and Warner (1980) conclude that" when events are not clustered in time, the differences between the various methodologies are quite small". They concluded that there is no evidence that more complicated methodologies beyond one factor model convey any benefit. Bar-Yosef and Brown (1977) estimated β_s around the event by using a moving window approach, and found that cumulative average residuals are computed exactly the same as shown by Brown and Warner (1980) for the market model. Several researchers, such as Thompson (1978), and Watts (1978) employed the moving window approach in event studies, and it provided the same interpretations, with Brown and Warner (1985) and Thompson (1988).

Daily returns models are drawn from a fat-tailed distribution with finite higher moments, such as the τ distribution or drawn as a mixture of distributions. The result is a fat-tailed unconditional distribution with a finite variance and higher moments. Since all moments are finite, the central limit theorem applies. Abnormal return is the actual ex post return of the security over the event window minus the normal return of the company over the event period. The normal return is defined as the return that would be expected if the event did not take place. For each company i and event date τ, I have

$$\epsilon_{it}^{*} = R_{it} - E\{R_{it}|H_t\}$$

(2)

where $\epsilon_{it}^{*}, R_{it},$ and $E(R_{it})$ are the abnormal, actual, and normal returns, respectively, for period $t.H_t$ is the conditioning information for the normal performance model. I used the market model to model normal returns or expected returns where H_t is the market return. The market model assumes a stable linear relation between the market and the security return.

Guidolin and Timmermann (2005,a and b) identify three states that can broadly be interpreted: a high-volatility "bear" state with large, negative mean returns, a "normal" state with returns closer to their historical averages, and a "bull" state with high mean returns on stocks and bonds. Specification tests that consider the full probability distribution of asset returns strongly reject single-state. Siganos and Chelley-Steeley's (2006) momentum anomaly states that shares that performed the best (worst) over the previous 3 to 12 months continue to perform well (poorly) over the subsequent 3 to 12 months. Evidence suggests that the strategy that buys previous winner shares and sells short past loser stocks can generate an abnormal profitability rate of approximately 1% per month (Jegadeesh and Titman, 1993). Griffin et al. (2003) reported that momentum profits tend to be stronger during down markets. Cooper et al. (2007) argued that momentum profits are more pronounced following up markets. Siganos and Chelley-Steeley's (2006) bull and bear markets are defined based on market return over various time horizons, and it is found that momentum gains are more pronounced following down markets.

The host market condition is a factor that will enable me to test my hypotheses. I define the host market condition proxy, $\overline{DJIA}_{(0,+50)}$, as the average DJIA index return for the post-listing period of (0 to +50) days. I chose this average index return as an indicator; as such, if the average index return was a positive in the post-listing period, then the host market condition is a positive, and vice versa. Since I am using the market model to estimate the normal return and used the daily index returns as the proxy for the market portfolio, then by definition the estimated normal return will reflect those host market conditions. In doing so, the estimated abnormal return should also reflect those host market conditions.

I used the ordinary least squares (OLS) method to estimate the market-model[2] parameters using the DJIA daily index returns as a proxy for the market portfolio returns. Scholes and Williams (1977, p. 324) level two criticisms regarding the use of OLS market model. The first issue is that the estimates of market-model parameters are biased and inconsistent; with daily data, the bias can be severe, and because of non-synchronous trading, daily returns can exhibit serial dependence. The second issue is the cross-sectional dependence of security-specific returns, as there is evidence that the variance of stock returns increases for the days immediately around the events.

Scholes and Williams (1977) and Dimson (1979) presented evidence that OLS estimates of β are biased. However, that does not necessarily imply misspecification in event study as long as there is no clustering of events. Brown and Warner (1985) indicate that there is no evidence that procedures other than OLS improve either the specification or the power of the tests. It is important to note that non-synchronous trading can induce serial correlation. Brown and Warner (1985) found that with a simple autocorrelation adjustment, no extensive changes occurred.

After estimating the abnormal return, I considered the aggregation of abnormal returns.[3] Dyckman et al. (1984) suggest that accumulating residuals has an advantage when uncertainty exists about the event date. The aggregation is along two dimensions—over time and across securities. I considered aggregation over time for an individual security and then considered aggregation both across securities and over time.

1.4.2 Hypotheses-testing Parametric Tests

1.4.2.1 Patell Test[4]

The literature also refers to the Patell test as a standardized abnormal return test or a test assuming cross-sectional independence. Many published studies use the Patell test (Linn and McConnell, 1983; Schipper and Smith, 1986; Haw, Pastena, and Lilien, 1990).

The test statistic for the null hypothesis that $CAAR_{T_1,T_2} = 0$ *is*

[2] See appendix A.1 for a complete description of the econometrics of estimating the market model using OLS.
[3] See appendix A 2 for the CAAR estimation using OLS

[4] See appendix B.2 for a detailed description of the test.

$$Z_{T_1,T_2} = \frac{1}{\sqrt{N}} \sum_{j=1}^{n} Z^j{}_{T_1,T_2}.$$

(3)

Under cross-sectional independence of $Z^j{}_{T_1,T_2}$ and other conditions, Z_{T_1,T_2} follows the standard normal distribution under the null hypothesis. If abnormal returns are serially uncorrelated, the variance $CAR_j$is the sum of the variances of daily abnormal returns.

Instead of using average standardized abnormal returns, the study reports precision-weighted cumulative average abnormal return. The precision-weighted CAAR, as a weighted average of the original CAR_s, preserves the portfolio interpretation that $CAAR$ offers but average $SCAR$ does not.

The Patell test statistics for abnormal returns cumulated over specific periods are not adjusted for serial dependence. Mikkelson and Partch (1988) perform such correction on collative returns. The serial dependence is not due to any presumed dependence in true market-model error terms, but occurs because all of the abnormal return estimators being cumulated are functions of the same estimators of the market-model parameters. The derivation of the corrected standard error used by Mikkelson and Partch (1988) requires that the abnormal return be interpreted as forecast error.

If abnormal returns are serially correlated then following Mikkelson and Partch (1988), the corrected test statistic for the null hypothesis that $CAAR = 0$ is

$$Z_{CAAR} = N^{\frac{-1}{2}} \sum_{j=1}^{n} \frac{CAR_{T_{1j},T_{2j}}}{S_{CAR_{T_{1j},T_{2j}}}}.$$

(4)

The corrected test accounts for the fact that within the window, the abnormal returns for each stock are serially correlated. Applications of the corrected test in addition to Mikkelson and Partch (1988) include Mais, Moore, and Rogers (1989), Cowan, Nayar, and Singh (1990), Mann and Sicherman (1991), and Lee (1992). The bias in the uncorrected test is small in event windows shorter than 60 days but serious in event windows longer than 100 days.

1.4.2.2 Cross-Sectional and Standardized Cross-Sectional Test[5]

With standard event study methodology, the test is focused only on the change in the mean of the company's return distribution: only the change in average returns is investigated. However, the change in the mean of the distribution also may be accompanied by a change in higher moments of the distribution. For example, on average, the arrival of new information may or may not have effect on a company's average return, but the company's average event-day release of information may increase the returns dispersion. Patell and Wolfson (1979), Kalay and Lowenstein (1985), Rosenstein and Wyatt (1990), and Boehmer et al.,(1991) all describe a significant increase in return's variance around an event, and in some cases the variance increases to more than a three-and-a-half times the variance on the estimation period (Dann, 1981).

[5] See appendix B.3 and B.4 for detailed descriptions about these two tests.

Cross-sectional tests are a standard part of almost every event study. They are relevant even when the mean stock price effect of an event is zero. One reason that abnormal returns vary cross-sectionally is that the economic effect of the event differs by company. For such a situation, Sefcik and Thompson (1986) examine the statistical properties of cross-sectional regressions. They argue that accounting for cross-sectionally correlated abnormal returns and heteroscedasticity in the abnormal returns is potentially important for inferences.

Abnormal returns also vary cross-sectionally, because the degree to which the event is anticipated differs by company. For example, for companies that are more closely followed (e.g., more analysts), events are more predictable, ceteris paribus. Further, events are endogenous, reflecting a company's self-selection in choosing the event, which in turn reflects insider information. In acknowledging these factors, it can be observed that the unexpected information provided by an event determines stock price effects, which can have consequences. For example, standard estimates of cross-sectional coefficients can be biased (Eckbo et al., (1990)).

The ordinary cross-sectional test is calculated by using the following equation

$$T_{CS} = \frac{\frac{1}{N}\sum_{i=1}^{N} AR_i}{\frac{1}{N(N-1)}\sum_{i=1}^{N}[AR_i - \frac{1}{N} * \sum_{i=1}^{N} AR_i]\hat{}2} .$$

(5)

When there is cross-sectional dependence, failure to make adjustments for it results in a systematic underestimation of the variance of mean returns, implying too many rejections of the null hypothesis—both when it is true and when an abnormal return is present (Beaver (1968), and Collins et al., (1982). Collins and Dent (1984) propose a generalized least squares technique when the variance of each company's abnormal return estimator increases proportionally during the event period. Froot (1987, 1990) suggests a method–of-moment's estimator that allows for event-induced heteroscedasticity. Perhaps the simplest solution to the problem of event-induced heteroscedasticity is that discussed by Boehmer et al., (1991). The abnormal returns estimates are first standardized by their estimated standard deviation (assuming no event-induced heteroscedasticity), based on the residual variance from the estimation period and the fact that they are prediction errors, as pointed out by Patell (1976). Then, the standard deviation of these standardized variants (SARs, standardized abnormal returns) is calculated cross-sectionally in the event period, and the significance of the estimate of the average standardized abnormal return average is tested using the cross-sectionally estimated standard deviation. In effect, this method assumes that the event-induced increase in variance is proportional for each company. Boehmer et al., (1991)find in simulations that with this method, the frequency of rejection of the null is essentially equal to the nominal size of the test when the null hypothesis of no abnormal performance is true. When the null is false, their method rejects the null more often than the other methods for which the true size of the test is equal to the nominal size. That is, their test is unbiased and more powerful than other well-specified alternatives.

Boehmer et al., (1991)introduce the standardized cross-section test and report its empirical properties. The test is the same as the Patell test except that there is a final empirical cross-sectional variance adjustment in place of the analytical variance of the total standardized prediction error (Sanders and Robins, 1991).

For day t in the event period, the test statistic is

$$Z_t = \frac{TSAR_t}{N^{\frac{1}{2}}(S_{SAR_t})}.$$

(6)

Then the standardized cross-sectional test statistic for the null hypothesis that $CAAR = 0$ is

$$Z_t = \frac{\sum_{i=1}^{n} SCAR_{T_{1j},T_{2j}}}{N^{\frac{1}{2}}(S_{SCAR_t})}$$

(7)

Brown and Warner (1985) report that the cross-sectional test is well-specified for event date variance, but not very powerful; however, Boehmer et al., (1991)report that the standardized cross-sectional test is more powerful and equally well-specified.

1.4.2.3 Crude Dependence Adjustments[6]

In addition, a problem with time-series dependence exists. Under the joint hypothesis that returns are given by the market model with stationary parameters and that the market is informational efficient, then according to Fama (1976), the disturbances in the market model, are independent across time. Neither the residuals nor the prediction errors from the market model are independent across time, as assumed in many event studies. As Mikkelson and Partch (1988) and Mais, Moore, and Rogers (1989) discuss, regression residuals (and, similarly, prediction errors) are correlated, since they are based on the same parameter estimates. To solve this problem, this study uses the crude dependence adjustments method.

Brown and Warner (1980, 1985) used a procedure called crude dependence adjustments whereby the standard error for this test is computed from the time-series of portfolio mean abnormal returns during the estimation period. Unlike the standardized abnormal return test, the time-series standard deviation test uses a single variance estimate for the entire portfolio.. The portfolio test statistic for day t in event time is

$$t = \frac{AAR_t}{\hat{\sigma}_{AAR}}.$$

(8)

The test statistic for $CAAR_{T_1,T_2}$ is

$$t_{CAAR} = \frac{CAAR_{T_1,T_2}}{\frac{\hat{\sigma}^2_{CAAR_{T_1,T_2}}}{\sqrt{N}}}$$

(9)

1.4.2.4 Bootstrapping

The use of bootstrapping involves repeatedly sampling from the actual data in order to empirically estimate the true distribution of a test statistic. This method was introduced first by Efron (1979), as a robust procedure for estimating the distribution of independent and identically distributed data. Since its

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[6] See appendix B.5 for a detailed description of this test.

inception, the bootstrap's performance under a variety of conditions has been examined in depth in the statistics literature. Work by Liu (1988) establishes the suitability of adopting the bootstrap under conditions most applicable to that of independent but not necessarily identically distributed observations.

If the random observations are drawn from distributions with similar means (but not necessarily identical variances) and the first two moments are bounded, use of the bootstrap is valid. In the context of event studies, Marais, and Laurentius., (1984) uses bootstrapped *p*-values to conduct inference in conjunction with the standardized residual approach, and (Lyon, Barber, and Tsai, 1999) and Horowitz (2001) use the bootstrapping method to perform non-parametric bootstrapping to determine the *p*-values of certain parametric tests, such as the Patell, standardized cross-sectional, time-series standard deviation, and cross-sectional tests. I employed this method in this study and used a re-sampling ratio of 0.25 and the bootstrap significance level was one-tailed.

1.4.2.5 Skewness-adjusted Transformed Normal Test

The transformed normal test produced by Hall (1992) is employed in this study to correct for skewness. First, I estimate the cross-sectional standard deviation and then calculate the skewness, arriving at the skewness-adjusted transformed normal test statistic:

$$t_1 = M + \frac{1}{3}\hat{\gamma}M^2 + 1/27\hat{\gamma}^2M^3 + \frac{1}{6N}\hat{\gamma}.$$

(10)

1.4.3 Hypotheses Testing: Non-parametric Tests

I will use non-parametric tests in order to avoid the misspecification errors that occur when using parametric tests when the assumption of normality is violated.

1.4.3.1 Generalized Sign Test[7]

The sign test is a simple binomial test of whether the frequency of positive abnormal residuals equals 50%. The generalized test is a refined version of this test that allows the null hypothesis to be different from 0.5. The advantage of the generalized sign test is that it takes into account the evidence of skewness in security returns.

$$GS = \frac{|P_0 - P|}{\sqrt{P(1-P)/_N}}$$

(11)

This test considers that both the sign and the magnitude of abnormal returns are important. For each window, I report the number of securities with positive and negative abnormal returns (cumulative abnormal returns as well); the null hypothesis for the generalized sign test is that the fraction of positive returns is the same as in the estimation period. The actual test uses the normal approximation of binomial

[7] See appendix B.6 for a detailed description of this test.

distribution. Sanger and Peterson (1990), Chen, Hu, and Shieh (1991), and Cowan (1992) also report that the generalized Z test is well-specified for event date variance increases and more powerful than the cross-sectional test. Cowan (1992) notes the generalized sign test controls for the normal asymmetry of positive and negative abnormal returns in the estimation period.

1.4.3.2 Rank Test[8]

Corrado (1989) describes the rank test for a one-day event window. The ranks of the abnormal returns of different days are dependent by construction. However, the effect of ignoring the dependence should be negligible for short-event windows. The rank test extends to multiple-day windows by assuming that the daily return ranks within the window are independent. The rank test procedure treats the combined estimation period and event period as a single set of returns, and assigns a rank to each day.

The rank test statistic for the event window composed of days T_1 through T_2 is

$$Z_r = (L)^{\frac{1}{2}} \left\{ \frac{\overline{K_{T_1,T_2}} - \breve{K}}{\left[\sum_{t=1}^{M+1} (\overline{K_t} - \bar{K})^2 \big/ _{(M+1)} \right]^{\frac{1}{2}}} \right\}.$$

(12)

1.4.3.3 Wilcoxon Signed Rank Test

The sign test is a non-parametric test, and its weakness is that it may not be well-specified if the distribution of cumulative abnormal returns is skewed, as can be the case with daily data. With skewed cumulative abnormal returns, the expected proportion of positive cumulative abnormal returns can differ from one-half even under the null hypothesis. The Wilcoxon test was designed by Frank Wilcoxon (1892–1965) to improve on the sign test. The actual test utilizes the Z distribution,

$$Z = \frac{w^+ - \frac{n(n+1)}{4} - \frac{1}{2}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}}.$$

(13)

1.4.3.4 The Jackknife Test[9]

The Jackknife test (Giaccotto and Sfiridis, 1996) incorporates the standardized abnormal return for each stock j, computed using the event period sample standard deviation.

The Jackknife test statistic for the sample of stocks on day t is

$$t_{Jackknife} = \frac{\overline{\Theta_t}}{\frac{s_{Jackknife,t}}{\sqrt{N}}}.$$

(14)

[8] See appendix B.7 for a detailed description of this test.
[9] See appendix B.8 for a detailed description of this test.

The distribution of $t_{Jackknife}$ under the null hypothesis is approximately normal with mean zero and unit variance. To test the significance of the CAAR over the window from date T_1through T_2, the Jackknife test statistic for the sample of stocks in window $(T_{1,}T_2)$ is

$$t_{Jackknife} = \frac{\overline{\Theta_{T_1,T_2}}}{\frac{s_{Jackknife,T_1,T_2}}{\sqrt{N}}}.$$

(15)

1.4.4 Fama-French Procedure

Up to this point, I have used the standard market model, as discussed in Brown and Warner (1985) and employed by Prabhala (1997), who demonstrated that the traditional event study approach generally performs well in a wide range of circumstances. Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994) note stock returns tend to be associated with company size as well as with book-to-market ratios. Fama and French (1992) demonstrate that these two factors (size and book-to-market equity) appear to describe well the cross-section of average stock returns in the United States. The proxy for company size is the natural logarithm of the value of the company's market equity at the end of the fiscal year prior to the date of the listing (where market equity equals price per share times the number of shares outstanding). The proxy for company book-to-market ratio is calculated, whereas the numerator equals the book value of the companies' common equity plus deferred taxes in the fiscal year prior to listing in the U.S. and the denominator equals the value of the company's market equity at the end of the fiscal year prior to the time of the listing. Dharan and Ikenberry (1995) examined the nature of post-listing stock returns by controlling for the size and the book-to-market, and they found that not only are abnormal returns negative following listing, but also that post-listing drift is more severe in magnitude and longer in duration than previously reported. The evidence indicates that the drift does not appear to be a consequence of miss-measured abnormal performance due to an improper choice of benchmark. They argued that their evidence is consistent with the hypothesis that managers time the market.

To complement testing the hypothesis in this study, I employed the Fama-French procedure, whereby its three-factor models are used as the return-generating process. The model is

$$R_{it} = \alpha + \beta_i R_{mt} + s_i SMB_t + h_i HML_t + \epsilon_{it}.$$

(16)

Then I define the abnormal return for the common stock ith company on day t as

$$A_{it} = R_{it} - (\hat{\alpha} + \widehat{\beta_i} R_{mt} + \widehat{s_i} SMB_t + \widehat{h_i} HML_t),$$

(17)

where the coefficients $\hat{\alpha}_i, \hat{\beta}_i, \hat{s}_i$, and $\hat{h}_i$ are the OLS estimates of $\alpha_i, \beta_i, \hat{s}_i$, and $h_{i.}$ See Fama-French (1993) for a detailed description of the model.

1.5 CHAPTER SCOPE

The simple answer to the question of why do companies cross-list is that companies cross-list to maximize their returns. However, the challenge to uncover was which type of returns are the companies that cross-list trying to maximize. Are they trying to maximize pre-listing returns, post-listing returns, or long-run returns? This chapter confirms previous research that there is a pre-listing run-up in price and, hence, an increase in pre-listing returns and confirms that on or around the cross-listing date, positive returns are observed.

This chapter aims to answer why companies' cross-list in terms of the post-listing returns, and the evidence presented shows that companies cross-list based on either a market-timing consideration or on a genuine performance consideration. This chapter did not attempt to explore the latter issue beyond the scope of this chapter, as it will be investigated in Chapter 3.

1.6 SAMPLE AND DATA

I conducted the analysis from 2003 to 2008. I chose this period to perform analysis on the most recent data available and to take advantage of changing market conditions in the host market (U.S. market). The study uses companies that had their shares listed in their home market or on any other stock exchange except the U.S. market before they cross-listed on the U.S. exchange. In addition, the sample did not include IPO companies, because the purpose is to examine the impact of cross-listing event on post-listing returns. Table 4 shows the list of companies used in the sample, their daily average return, and the corresponding host market index return (DJIA).

$< Insert\ Table\ 4 >$

I collected the data for non-U.S. companies listing in the U.S. exchange market along with the listing dates from the NYSE and the NASDAQ fact book, and then verified those dates from the Center for Research and Security Prices (CRSP). Moreover, I checked the World Scope database and the Thompson Reuter's database to verify the foreign country and foreign stock exchange as well. I collected pre-listing daily prices from the Thomson Reuters database and post-listing daily prices from CRSP daily stock prices tape and verified it through the Thomson Reuters database. I used the closing price of the stock at each day and matched the daily price with the daily price of the market index. The collection of daily stock prices and daily market index process will help determine the daily stock return and the daily market index return, respectively. By nature, a pre-listing return is a foreign daily stock return, and it is calculated by the change in prices without dividends. I have transformed daily foreign prices to U.S. dollar currency at their respective dates using the exchange rates that were prevalent at that time, verified using the Thomson Reuters database.

In order to obtain a U.S. listing, a foreign company must file a formal application with the U.S. exchange. It usually takes about four weeks for the NYSE and only a few days for the NASDAQ to approve or reject the application. The submission of a formal application for the NYSE listing is announced in weekly bulletins published by each exchange on the first day following the application. The first public announcement concerning an application for NASDAQ listing is made electronically through the NASDAQ terminals worldwide when the application is approved. Thus, the submission of the NASDAQ application itself is not formally announced. Unlike the NYSE, NASDAQ does not require a confidential preliminary review of eligibility. Once the application to the NYSE or NASDAQ is approved, the company—in consultation with the exchange—decides on the date when the company's stock will be actually listed.

For non-U.S. companies, a cross-listing announcement's importance derives from its strong indication of management's confidence in its company's global operations. Moreover, the cross-listing application acceptance carries another positive sign, this time by the foreign stock exchanges, regarding the company's ability to compete internationally by cross-listing abroad. Additionally, Lau at el. (1994) find that price reactions are most likely to happen on the first trading day and not on either the cross-listing application or acceptance dates. For unseasoned stocks listed in the United States and then cross-listed abroad, Valero at el. (2009) analyzed the stocks' behavior around the listing day rather than the announcement dates, due to difficulties in identifying the exact announcement dates. Out of 209 cross-listed stocks abroad they have in their full sample, they identified the exact cross-listing dates for only 46 stocks, finding significant positive average abnormal returns on the day before cross-listing and significant positive accumulative average abnormal return on the day of cross-listing. I will not examine the announcement effect, because sometimes a company spokesperson may indicate steps to cross-list, then a few months later will make additional announcements about new steps or negotiations being finalized. Therefore, it is difficult to consider the announcement date as a definite marker; hence, the pre-announcement estimation period and event date will be continuously evolving, so the event date will be the actual listing date.

The sample began with 240[10] non-U.S. companies that cross-listed in the United States either on the NYSE or NASDAQ during the period from 2003 to 2008. The criteria for pre-listing period is such that the estimation period would be from –545 to –51 days before the event date (listing date), and the post-listing period to be at least 365 days after the listing date. I chose a long pre-listing period to have an econometrically valid analysis and for the post-listing period range, I wanted to insure the continuity of the stocks after they get cross-listed in order to have valid inferences drawn from the analyses. The sample resulted in 32 non-U.S. companies from eight different countries.

1.7 EMPIRICAL RESULTS

1.7.1 Empirical Results (Parametric)

Table 5 shows the result of testing in which the post-listing anomaly exists, that is, there are significant negative post-listing abnormal returns. I report that in the days of (+11, +50) post-listing period, the mean cumulative abnormal return is –21.39%, with a significant negative Z Patell test of –2.598, a time-series cross-sectional test (hereafter, TCS) with significant negative –1.645, and a skewness-corrected t-test (hereafter, SCT) with significant negative of –1.874. Based on those results, I conclude that the post-listing anomaly exists for some companies.

[10] There were 145 companies which cross listed as an IPO and that was one of the biggest reasons the sample dropped from 240 to 32 companies.

< *Insert Table* 5 >

Table 6 shows the results of testing in which the post-listing anomaly does not exist, that is, there are significant positive post-listing abnormal returns. I report that in the days of (+11, +50) post-listing period, the mean cumulative abnormal return is 4.70%, with a significant positive Z Patell test of 1.876, and a Z -standardized cross-sectional test (hereafter, ZSTD) with a significant positive of 1.761. Based on those results, I conclude that the post-listing anomaly does not exist for some companies, which casts doubt on the validity of the anomaly, because some companies do not show such an anomaly.

< *Insert Table* 6 >

The next step of the analysis is testing whether some companies time the market, while others do not. In doing so and as explained earlier in the research method, I connect the post-listing anomaly and market timing by the host market condition. That is, the analysis is presented twofold. First, the post-listing anomaly exists, while the host market condition is either a positive or a negative. Second, the post–listing anomaly does not exist, while the host market condition is either a positive or a negative.

Table 7 shows the case in which the host market condition is a negative given by the average returns of the DJIA index over the period of (0, +50). I report that in the period of (+11, +50), the mean cumulative abnormal return is –37.96%, with significant negative Z Patell, TCS, and ZSTD of –3.410, –2.425, and –2.587, respectively. I conclude that since the host market condition is a negative and the post-listing abnormal return is a negative (post-listing anomaly), then the host market condition explains the anomaly, and companies do not time the market, because they cannot be timing a market that is down.

< *Insert Table* 7 >

Table 8 shows the case in which the host market condition is a positive given by the average returns of the DJIA index over the period of (0, +50). I report that in the period of (+11, +50), the mean cumulative abnormal return is –23.08% with significant negative Z Patell, TCS, and ZSTD of –1.661,–3.777, and –3.462, respectively. I conclude that since the host market condition is a positive and the post-listing abnormal return is a negative (post-listing anomaly), then the host market condition does not explain the anomaly, and those companies time the market. I made that assessment, because those companies should have achieved positive post-listing abnormal returns since the host market has favorable conditions, and based on the various reasons they cited for cross-listing, such as a declining cost of capital, broader investor base, more transparency, and so forth. The reason they did not achieve positive post-listing abnormal returns, and instead achieved significant negative post-listing abnormal returns, is the market participants have recognized that those companies' motives for cross-listing were nothing more than taking advantage of an up-market in the host market (market timing).

< *Insert Table* 8 >

Table 9 shows the case in which the host market condition is a positive given by the average returns of the DJIA index over the period of (0, +50). I report that in the period of (+11, +50), the mean cumulative abnormal return is 9.65%, with significant positive Z Patell, TCS, and ZSTD of 2.678, 2.902, and 2.761, respectively. I conclude that since the host market condition is a positive and the post-listing abnormal return is a positive (there is no post-listing anomaly), then the host market condition can explain the positive abnormal returns for those companies. Since the host market conditions are favorable, I cannot conclude whether or not these companies time the market; thus, the evidence is inconclusive. I made that assessment, because those companies could have achieved positive post-listing abnormal returns, regardless of the host market condition, or they may have achieved those positive abnormal returns, because of the favorable host market conditions.

$< Insert\ Table\ 9 >$

Table 10 shows the case in which the host market condition is a negative given by the average returns of the DJIA index over the period of (0, +50). I report that in the period of (+11, +50), the mean cumulative abnormal return is 3.47% with insignificant positives across all test statistics. I conclude that since the host market condition is a negative and the post-listing abnormal return is a positive even though it is insignificant (there is no post-listing anomaly), then the host market condition cannot explain the positive abnormal returns for those companies. Since the host market conditions are unfavorable, I can conclude that these companies do not time the market, because they cannot be timing a market that is negative. Further, the insignificant negative may have resulted from unfavorable timing conditions at the date of cross-listing.

$< Insert\ Table\ 10 >$

1.7.2 Empirical Results (Non-Parametric)

Tables 11 through 16 show the same results as were discussed in Tables 7 through 10, but in the former, I used non-parametric tests such as the generalized sign *Z* test and the rank *Z* test, the Jackknife test, and the signed rank test. The use of non-parametric tests is to confirm the results I discussed earlier, which are some companies time the market, while other companies do not.

$< Insert\ Tables\ 11 - 16 >$

1.7.3 Empirical Results (Fama-French Estimation Procedure)

As discussed in the section on research methodology, I used another estimation procedure aside from the market model to estimate abnormal returns, the Fama-French procedure, in which they control for size and book-to-market ratio. Tables 17 through 22 show the same results as were discussed for Tables 7 through 10. Those results confirm the findings reached through using the market-model approach and add confirmation to the conclusion reached, that is, some companies time the market, while other companies do not.

$< Insert\ Tables\ 17 - 22 >$

1.8 SUMMARY AND CONCLUDING REMARKS

The simple answer to the question why do companies cross-list is that companies cross-list to maximize their returns. However, the challenge was which type of returns are the companies that cross-list trying to maximize. Are they trying to maximize pre-listing returns, post-listing returns or long-run returns? This chapter confirms previous research that there is a pre-listing run-up in price and, hence, an increase in pre-listing returns and confirms that on or around the cross-listing date, positive returns are observed.

This chapter aims to answer why companies cross-list. I attempted to answer that question in terms of the post-listing returns, and the evidence presented in this chapter shows that companies cross-list based on either a market-timing consideration or a genuine performance consideration. This chapter did not attempt to explore the genuine performance consideration issue, will do so in Chapter 3. This chapter elaborated on the other side of the issue, which is, companies cross-list because of market-timing consideration, and not only did the evidence show that some companies time the market, while others do not, but also explains the "post-listing anomaly." The sample evidence shows the host market condition plays an important role in answering the combined questions of why companies cross-list and why there is a "post-listing anomaly." On the one hand, the evidence reveals companies that cross-list in a host market while that market condition is "positive" and achieve significant negative post-listing abnormal returns are companies that are timing the market, and that is why the anomaly exists. On the other hand, the evidence reveals if companies cross-list in a host market while that host market condition is "negative" and achieve positive post-listing abnormal returns whether significant or not, then those companies are not timing the market, because why would they time a market that is down? Moreover, this demonstrates that the "post-listing anomaly" does not exist, which indicates that it is not an anomaly, at least not for this sample.

This chapter opens up the field for additional research questions, such as does benchmark matter in determining the abnormal returns; does the selection of a different host market index affect the results; is there evidence of earnings management for companies that time the market; is there an increase in company value in terms of Tobin's-Q when companies cross-list, especially if those companies time the market; does the market overreact to cross-listing; and finally what are the main drivers for CAAR.

CHAPTER 2
DOES THE CHOICE OF BENCHMARKS MATTER?
THE CHARACTERISTIC INDEX VERSUS THE MARKET INDEX

2.1 INTRODUCTION

Event study methodology is used to estimate abnormal returns across different firms using a firm-specific event that is time independent across different firms. In that way, we can aggregate the abnormal returns around the period we wish to examine and then use statistical tests to test our hypotheses. Brown and Warner (1980) conclude that" when events are not clustered in time, the differences between the various methodologies are quite small". Conducting event studies requires selecting data randomly from different securities; as such, they are characteristically non-representative of the overall market. Most event studies group securities based on certain traits such as size, momentum, and book-to-market ratio. Ahern (2009) suggests that the results of Brown and Warner (1980, 1985) may not hold in actual event studies, because the average market results will not hold. He also found that the characteristic-based benchmark model, in which stock returns are adjusted by a matched size-return portfolio of control stocks, displays the least bias of all the models.

This chapter investigates whether the choice of different benchmarks and/or different estimation procedures makes a difference in the sign and the significance of post-listing abnormal returns; hence, instead of drawing samples randomly, I draw samples non-randomly. In particular, samples are drawn based on certain characteristics, such as low book-to-market ratios and high book-to-market ratios (LOBTM, HIBTM), size, and portfolios of book-to-market ratios and size. In addition, based on behavioral finance concepts, I formed portfolios on short-term reversal (STR) factors, long-term reversal (LTR) factors, the sentiment factor, and finally momentum factor. For the estimation procedure, I used the market model estimated by OLS, the Scholes-Williams model of betas estimates, and the market model estimated by GARCH (generalized autoregressive conditional heteroscedasticity), to calculate the post-listing abnormal returns. In addition, I used different benchmarks both as a proxy for index returns and for the host market condition indicator, As such, each benchmark corresponds to the characteristic of the portfolio formed for each analysis. For example, when I form a portfolio based on a LTR benchmark, then I use the LTR index returns to calculate and estimate abnormal returns, and the average of LTR index returns as an indicator of the host market condition. As such, if the average LTR index returns for the period under investigation is a negative, then the host market condition is a negative and vice versa. I used both parametric and none-parametric tests, to determine if different methods will produce different results, I also investigated the effect of using post-event versus pre-event data to estimate the model parameters.

Although there are a variety of other procedures to calculate the abnormal returns such as the comparison period portfolio method, market-adjusted returns, unadjusted market returns (raw returns), and returns across securities and time (RATS), I did not show results for those methods because they are statistically inferior to the Scholes-Williams and GARCH methods. Using daily returns data, it will be shown that GARCH is a better fit.

The analyses were built on the results of the previous chapter, in which I showed that the host market condition explains the post-listing anomaly. Therefore, the first set of hypotheses in this chapter tests whether the post-listing anomaly (significant negative post-listing abnormal returns) exists regardless of the estimation procedures or the benchmarks used, and the second set of hypotheses are to test whether the selection of different benchmarks and different estimation procedures affect the sign and the significance of the post-listing abnormal returns. In other words, if I used different a benchmark index and different estimation procedure, would I still reach the conclusion that some firms time the market while others do not, or were my conclusions reached in the first chapter reached because of improper use of both the benchmark index and the estimation procedure.

In the previous chapter, I showed that post-listing abnormal return is not an anomaly and can be explained within the context of the host market condition. In addition, I drew conclusions about the motives of cross-listing, in particular, companies either time the market before they cross-list or they cross-list based on a genuine performance consideration. This chapter finds that, on the one hand, for some of the different characteristic index benchmarks used, different estimation procedures changed the sign and the significance of post-listing abnormal returns. On the other hand, for all the different market index benchmarks used, different estimation procedures did not change the sign or the significance of post-listing abnormal returns. Moreover, the characteristic index benchmark is a better fit when forming portfolios based on certain characteristics, and the GARCH model is superior in estimating the market-model parameters—more so than any other method.

This chapter contributes to the literature in several ways. First, I confirm that the post-listing anomaly can be explained in the context of the host market condition. Second, I show a comprehensive review of using different benchmarks and different estimation procedures in calculating and estimating the abnormal returns, and show that those changes affect the sign and the significance of the post-listing abnormal returns. Third, I show that GARCH is the best estimation procedure when using daily returns, and the use of the characteristic index is a better fit when forming portfolios of companies based on certain characteristics.

This chapter leaves open several important research questions, such as: is there any evidence of earnings management for companies that time the market; is there an increase in company value in terms of Tobin's-Q when companies cross-list, especially if those companies time the market; does the market overreact to cross-listing; what are the main drivers for the CAAR; and several others. I will investigate some of those questions in Chapter 3.

2.2 LITERATURE REVIEW

In the two-parameter portfolio model of Tobin (1958), Markowitz (1952), and Fama (1965b), the expected return on a security depends only on β. Fama and MacBeth (1973) state that they cannot reject the hypothesis that risk averse investors hold efficient portfolios and no measure of risk other than portfolio risk systematically affects average returns. Fama-MacBeth (1973) hypothesized that the process of price formation in the capital market is dominated by growth optimizers. That is, the market portfolio is growth optimal and that the hypothesis cannot be rejected. Ross (1976) introduced the multifactor model (APT) alternative to the CAPM, but its shortcoming is that it provides exact predictions of expected returns only for portfolios whose returns are completely captured by the common risk factors. Merton (1973) develops an inter-temporal model (ICAPM) that uses utility maximization to get exact multifactor predictions of expected security returns and obtains results without assuming the market portfolio is perfectly diversified. Merton (1973) shows the CAPM is a special case of the ICAPM, but it lacks the simple intuition that makes the CAPM attractive.

Fama (1976) and Roll (1978) report that there is little relation between U.S. common stock returns to either the market βs of the Sharpe (1964)–Lintner (1965) asset pricing model or the consumption βs of the ICAPM (Breeden, Gibbons, and Litzenberger (1989). Consequently, market β is not sufficient to describe expected return. On the other hand, variables that have no special standing in asset pricing theory show reliable power in explaining the cross-section of average returns. Those variables are *E/P*, *C/P*, *BE/ME*, and *Size* (Banz, 1981; Basu, 1983; Bhandari, 1988). Fama and French (1992) show the joint roles of market β, *Size*, *E/P*, *Lev*, and *BE/ME* in the cross-section of average returns, and they find that used alone or in combination with other variables, β offers little information about average return. In addition, they suggest in combination *Size* and *BE/ME* seem to absorb the apparent roles of *Lev* and *E/P* in average returns. There are patterns in average stock returns that are considered anomalies. For example, Banz (1981) finds that small stocks have high average returns. (Rosenberg, Reid, and Lanstein, 1985; Chan, Hamao, and Lakonishok, 1991; and Fama and French, 1992) report that stocks with high book /market ratio has high average returns. Haugen and Baker (1996) and Cohen, Gompers, and Vuolteenaho (2002) find that higher stocks returns are associated with profitability, while Fairfield, Whisenant, and Yohn (2003) and Titman, Wei, and Xie (2004) show that contrary to common logic more investments by firms may lowers stock returns for those firms. Jegadeesh and Titman (1993) document that there is a momentum effect such that stocks with low returns will have low returns in the future , while stocks with high past returns will have high future returns. In response to the pricing anomalies of the CAPM discussed above, alternative pricing models have been developed, although their use in short-run event studies has been limited. In particular, Fama and French (1995) use a three-factor model including a market index, size index (SMB-small minus big), and book-to-market index (HML-high minus low) to explain stock returns. Carhart (1997) uses a four-factor model that appends the Fama–French three-factor model with a short-run momentum index.

Lakonishok, Shleifer, and Vishny (1994), Haugen, and Baker (1996), and MacKinlay (1995) argue that the premium for relative distress, the difference between the average returns on HIBTM and LOBTM stocks is too large to be explained by rational pricing and overreaction must be the reason for that premium. They conclude that the premium is usually positive and close to an arbitrage opportunity. Fama and French

(1995) argue, however, that overreaction cannot be the whole story, since the high distress premium in returns persists for at least five years after portfolio formation, but the mean reversion of earning growth is apparently much sooner. In addition, the argument presented by Kothari, Shanken, and Sloan (1995) was dismissed because of the direct evidence presented by Chan, Jegadeesh, and Lakonishok (1995) concerning survivor bias. The three-factor model failed to capture the continuation of short returns documented by Jegadeesh and Titman (1993). It may be this particular anomaly is the spurious result of data snooping or that asset pricing is irrational. Investors under-react to short-term past information, which produced return continuation, but they overreact to long-term past information, which produces return reversal. The evidence of Kahneman and Tversky (1982, 1981) and others, which forms the foundation of existing behavioral finance models, predicts overreaction and return reversal. The last explanation is that asset pricing is rational, which means that the three-factor model is just a model, and it has its shortcomings.

Leroy (1973) and Lucas (1978) have shown that random walks of assets returns is not necessary a condition of economic equilibrium. Lo and MacKinlay (1988) have shown that stock prices do not follow random walks. Richardson (1989, 1990) asserted that stock prices are serially correlation estimates that are statistically indistinguishable from zero.

Fabozzi and Francis (1977) found that there is no difference in the model estimates between bull and bear market conditions. In contrast, Goldberg and Vora (1981) find that model estimates vary with the market condition. Klein and Rosenfeld (1987) further support their argument. Robichek, and Myers (1966), and Epstein and Turnbull (1980), show that uncertainty plays a significant role in determining the expected returns of stocks

2.3 HYPOTHESES DEVELOPMENT

According to Ahren (2009), because I am using daily securities returns along with daily market index returns to estimate the abnormal returns, and since daily returns are usually positively skewed and asset pricing models characterized by omitted variables bias, then, if the standard event study is characterized by factors related to pricing bias, the abnormal returns estimated by the standard event study methodology are potentially biased, even though the standard event study methodology includes an intercept term. As such, if the slope coefficient is biased, then the intercept term adjusts so that the fitted line predicts the mean company returns. If it is realistic to expect to observe the average daily market return on any given day, then the model will not be biased, even if the market returns were higher or lower than the average returns, since they will cancel each other out. Since daily returns are skewed, however, then it cannot be expected to observe the average daily market return on any given day. Because of that and the omitted variable bias, the standard event study methodology will generate incorrect predictions on average, even when the model allows for an endogenously determined intercept, and this bias will even persist in larger samples (Ahren, 2009). Studies by Brown et al. (1995), and Dimson and Marsh (1986) suggest that a robust prediction technique must be used to avoid the bias in standard event study methodology.

Chan et al. (1985), Chen et al. (1986), assert that macroeconomic variables can explain stock returns. In particular, Liew and Vassalou (2000) suggest that HML and SMB contain information useful in predicting future GDP growth. Aretz et al. (2007) offers results that suggest the stock characteristics underlying the Fama and French (1993) model and the Carhart (1997) model are associated with six macroeconomic state variables. Vassalou (2003) and Liew and Vassalou (2000), found that book/market ratio is associated with changes in economic growth. Hahn and Lee (2005), and Petkova (2005), found that book/market ration is associated with variation in exposures to the term-structure slope, and that firm size, is negatively associated with exposures to changes in the survival probability. Banz (1981) finds that the CAPM predicts returns that are too low for small firms. Basu (1983) shows that price to earnings is negatively related to returns after controlling for market beta.

When the sample of event studies are formed based on certain characteristics, then I will be able to see if those characteristics make a difference in the estimation of the abnormal returns and on the testing of abnormal returns as well. Ahren (2009) reports that characteristic-based benchmark model, is the best model to use in event study methodology since companies are distinct in their characteristics, especially when they undergo specific events like cross-listing.

The results that were produced in chapter one were developed by using the benchmark DJIA as the reference portfolio to estimate and calculate the abnormal returns, and the same benchmark index was used as a host market indicator as well. As such, if the average benchmark index return for the period under investigation is a negative then the host market condition is a negative and vice versa. That analysis conducted in chapter one falls under the market index–based analysis.

In this chapter, I formed portfolios on *BE/ME* (BTM-book to market ratio) where *BE/ME* < 0 (not used); bottom 30%, medium 40%, and top 30%, then I used the benchmarks portfolios that is constructed by Fama and French as the reference portfolio to estimate and calculate the post-listing abnormal returns. This analysis I call the characteristic index–based analysis.

I also formed portfolios based on size, where *ME*< 0 (not used), small is from 1% to 50%, and big starts at 51%. The reason I did not form small, medium, and big quintiles as I did for the *BE/ME* portfolios is because my sample did not provide sufficient data to form those quintiles. For each of these portfolios, I use the size of the benchmark portfolios that are constructed by Fama and French as the reference portfolio to estimate and calculate the post-listing abnormal returns. This analysis I call the characteristic index–based analysis.

I constructed six portfolios (S/L, S/M S/H, B/L, B/M, and B/H). For example, S/L is a portfolio containing the stocks in a small market equity (ME found by multiplying the number of shares outstanding by the share price) group that are also in the *BE/ME* group. To avoid survivor bias (Breen and Banz, 1986), I do not include firms until they have appeared on Compustat for two years. The *BE/ME* breakpoints I used to form those portfolios are the same break points that Fama and French used to form their benchmarks portfolios, which are 30th percentile that represents low *BE/ME* ratio and 70th percentiles that represents the high *BE/ME* ratio, and the range of 31th percentile to 69th percentile is medium *BE/ME* ratio. For each of these portfolios, I use Fama and French's six portfolios formed on size and book-to-market as the reference portfolios to estimate and calculate the post-listing abnormal returns. Those six portfolio benchmarks are the intersections of two portfolios formed on size (ME) and three portfolios formed on the ratio of book equity to market equity (BE/ME). This analysis I call the characteristic index–based analysis.

Expected utility theory is based on rational decision making. However, subsequent confirmations showed systematic violations of expected utility as such people are irrational. Camerer (1995, 1998) discusses different forms of utility functions that are derived from irrational choice making. In prospect theory, Kahneman and Tversky (1979), and Tversky and Kahneman (1992) note that "individuals maximize a weighted sum of 'values' analogous to utilities, where the weights are functions of possibilities instead of true probabilities. Extremely low probabilities are treated as impossibilities and extremely high probabilities as certainties." Camerer (1998) argues that a form of prospect theory fits the data better than the customary utility theory.

Jegadeesh and Titman (1993) discusses what he called the momentum effect such that the appearance of positive abnormal returns to positive momentum firms, and negative abnormal returns to negative or low momentum firms. Jegadeesh and Titman (1993, 2001) and Chan, Jegadeesh, and Lakonishok (1995) report that investors routinely under-react and that under-reaction to market news is the prime source of the price momentum. Cusatis et al. (1993), Desai and Jain (1997), and Ikenberry et al. (1996) document instances where there is a price under reaction. Lakonishok and Vermaelen (1990) and Rouwenhorst (1998) find significant price momentum for an intermediate time horizon for stocks in 12 European countries during the period between 1980 and 1995. Aretz et al. (2007) analyses reveal that momentum-sorted portfolios have very different exposures to different sets of economic state variables. Da and Gao, (2005) assert that the link between realized returns and momentum or market irrationality and investors' behavioral biases (Daniel et al., 1988; Daniel and Titman, 2004) are related to market micro structure. Rouwenhorst (1999) discovers significant price momentum based on a six-month performance of the stocks in 17 of the 20 emerging markets worldwide studied for the period spanning from the 1980s to the 1990s. Research by Jegadeesh and Titman (2002), Scheinkman and Xiong (2003), and Sagi and Seasholes (2007) suggests that momentum strategies of buying prior winners and selling prior losers earn significant abnormal returns in the medium formation periods of less than one year.

According to Baker and Wurgler (2007), momentum is the cumulative raw return for the 11-month period from 12 through 2 months prior to the observation return. Momentum is the return on high momentum stocks minus the return on low momentum stocks where momentum is measured over months (–12, –2). Fama and French use six equal-weight portfolios formed on size and prior (–251,–21) returns to construct momentum. The portfolios, formed monthly, are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on prior (–251, –21) return. Momentum is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. I form portfolios using the momentum concept; as such, I form a portfolio whereby the companies in that portfolio exhibit positive momentum, and hence I will expect that those portfolios should exhibit positive momentum after they cross-list. Indeed, I expect that the average return will be even higher than what was expected from momentum predictions alone; as such, I expect positive post-listing abnormal returns. In addition, I use the momentum index provided by Fama and French as an indicator of the market condition where if the momentum index was a negative then the market condition is a negative and vice versa, and I use the index as the benchmark index to calculate abnormal returns. I call this type of analysis the characteristic index–based analysis.

I also investigate the post-listing abnormal return using both the momentum index as a market condition indicator and the reference index to calculate and estimate abnormal returns, but without forming portfolios on positive momentum; I call this case the market index–based analysis.

Graham and Dodd (1934) suggested because the market as a whole tends to overreact to negative news, some firms' stocks temporarily become undervalued and thus represent buying opportunities. DeBondt and Thaler (1985, 1987) present evidence of economically important return reversals over long intervals, and they explain it as investor overreaction, which is a general prediction of the behavioral decision theory of Kahneman and Tversky (1982). Some studies have found support for contrarian approaches to investment under certain market conditions (Basu, 1977). The contrarian profits were represented as a long-run phenomenon, but Jegadeesh (1990), Lehmann (1990), and Chopra, Lakonishok, and Ritter (1992), among others have shown that contrarian profits also exist in both short (weekly) and long (three to five years) horizons.

Fama and French built two additional momentum factors: one is STR built like the momentum index, but the prior return is measured from day (–20, –1), and the other factor is LTR where the prior return is measured from day (–1,250, –251). I use each of these two factors as a market condition indicator and form separate portfolios based on prior beliefs of those two factors. As such, I form a portfolio based on a negative LTR and expect that, according to the theory, those returns will reverse to be positive; hence, I expect positive post-listing abnormal returns. I also form portfolios following the same logic of LTR but this time on STR. As such, I form portfolios based on a negative STR and expect, according to the theory, that those returns will reverse to be positive; hence, I expect positive post-listing abnormal returns. I use the LTR index provided by Fama and French as an indicator of the market condition, where if the LTR index was a negative, then market condition was a negative and vice versa. In addition, I use the STR index provided by Fama and French as an indicator of the market condition where if the STR index was a negative, then market condition was a negative and vice versa. Each index is used as the benchmark index to calculate abnormal returns in each case. I call this type of analysis the characteristic index–based analysis.

I also investigate the post-listing abnormal return using the LTR index as a market condition indicator but without forming portfolios on prior beliefs and call this case the market index–based analysis. I also investigate the post-listing abnormal return using the STR index as a market condition indicator but without forming portfolios on prior beliefs and call this case the market index–based analysis.

An additional behavioral factor that is based on the prospect theory is sentiment. There is a number of proxies for sentiment to, but there are no definitive or uncontroversial measures; so, I use the Baker et al., (2006).sentiment index, which is based on the first principal component of six (standardized) sentiment proxies over 1962–2008 data in which each of the proxies first has been orthogonalized with respect to a set of macroeconomic conditions. Those variables are: *PDND,* a value-weighted dividend premium defined following Baker and Wurgler (2004) (values differ slightly from theirs due to subsequent improvements in the CRSP/Compustat merge procedure); *NIPO,* an IPO volume from Ibbotson, Sindelar, and Ritter (1994); *RIPO* is the first day returns on IPOs from Goetzmann and Ibbotson (1994), and Ibbotson, Sindelar, and Ritter (1994); *CEFD*, a closed-end fund discount, which is the average difference between the *NAV* of closed-end stock fund shares and their market prices. Previous researches suggest that CEFD is inversely related to sentiment. Zweig (1973) uses it to forecast reversion in DJIA stocks, and Lee, Shleifer, and Thaler (1991) argue that sentiment is behind various features of closed-end fund discounts. *SHARE* is an equity share in new issues defined following Baker and Wurgler (2000); and finally *TURN* is the NYSE turnover from the NYSE fact book. Baker and Stein (2004) suggest that turnover, or more generally liquidity, can serve as a sentiment index. In a market with short-sales constraints, irrational investors participate, and thus add liquidity, only when they are optimistic; hence, high liquidity is a symptom of overvaluation. Supporting this, Jones and Lamont (2002) finds that high turnover forecasts low market returns. *TURN* is calculated as the natural log of the raw turnover ratio, de-trended by the five-year moving average. The sentiment index provided by Baker et.al., (2006) acts as an indicator of the market condition in which if the sentiment index was a negative, then market condition was a negative and vice versa. In addition, I use the index as the benchmark index to calculate and estimate abnormal returns. I call this analysis the market index–based analysis.

Estimation procedures can use either pre or post event period. Mandelker (1974) use both pre- and post-event estimation period data on mergers. Copeland and Mayers (1982) use post-event data. Agrawal et al. (1992) and Gregory (1997) use post-event estimation data in long-run studies of mergers. This chapter estimates all models with separate pre and post-event estimation windows. Unless otherwise noted, all results presented in this chapter will be generated using pre-event data, as this procedure is more conventional.

The starting set of hypotheses begins when I test whether the "post-listing anomaly" exists given different choices of benchmarks and estimation procedures. In doing so, the logic posits if the host market was a positive and yet post-listing CAAR was a negative, then the "post-listing anomaly exists." Because I am using different benchmarks, as a proxy for the host market condition, and the same is used in the estimation procedure to determine abnormal returns, therefore the results will be consistent, and I will be able to draw valid inferences from my tests:

H_0: Post-listing anomaly exists regardless of benchmark types

H_A: Post-listing anomaly does not exist regardless of benchmark types

The following hypotheses all for drawing conclusions regarding the motives of companies to cross-list by relating the host market condition to the post-listing returns or, in other words, to the post-listing anomaly:

H1$_A$: Companies time the market

H1$_B$: Companies do not time the market

H1$_B$: Companies do or do not time the market (inconclusive)

The following hypotheses re-examine the relationship between host market condition, post-listing anomaly, and market timing when using different benchmarks and estimation procedures:

H2$_A$: Different benchmarks and different estimation procedures produce the same results

H2$_B$: Different benchmarks and different estimation procedures produce different results

It is important to note that these hypotheses will be tested simultaneously, because they are interrelated and for space considerations as well.

2.4 RESEARCH METHOD

I will use the same research method that I used in chapter one except in this chapter the host market condition is represented by different proxies that correspond to the specific benchmarks I used for each analysis. I define the host market condition proxy, *Size* as the average portfolio returns from day (0) to (+50) days that is formed on size; *BE/ME* as the average portfolio returns from day (0) to (+50) days that is formed on *BTM(book to market ratio)* and size; *BTM* as the average portfolio returns from day (0) to (+50) days that is formed on the book-to-market ratio; *Momentum* as the average portfolio returns from day (0) to (+50) days that is formed on momentum; *Sentiment* as the average portfolio returns from day (0) to (+50) days that is formed on sentiment index; *LTR* as the average portfolio returns from day (0) to (+50) that is formed on the LTR index; and *STR* as the average portfolio returns from day (0) to (+50) days that is formed on STR. I define the host market condition indicator, as such, if the average index return after the listing date (0, +50) was a positive, then the host market condition was a positive. Since I am using the market model to estimate normal returns and used the daily index returns as the proxy for the market portfolio, then by definition the estimated normal return will reflect those host market conditions; by doing so, the estimated abnormal return should also reflect those host market conditions as well.

At first, I used the OLS method to estimate the market-model parameters using—as described above—each of the daily index returns acting as a proxy for the market portfolio returns. In order to address the criticism to the market-model approach described in the first chapter and to address the issues raised about the standard event study methodology, however, I will use other estimation procedures described below.

2.4.1 Market Model with Scholes-Williams' Beta Estimation

Scholes and Williams (1977) used a different method to estimate the beta:

$$\hat{\beta}_j^* = \frac{\hat{\beta}_j^- + \hat{\beta}_j + \hat{\beta}_j^+}{1+2\hat{\rho}_m},$$

(18)

where $\hat{\beta}_j^-$ is the OLS slope estimate from the simple linear regression of R_{jt} on R_{mt-1}, $\hat{\beta}_j^+$ is the OLS estimate from the regression R_{jt} on R_{mt+1}, and $\hat{\rho}_m$ is the estimated first-order autocorrelation of R_m. As in OLS, the intercept estimator forces the estimated regression line through the sample mean:

$$\hat{\alpha}_j^* = \bar{R}_{jEST} - \hat{\beta}_j^* \bar{R}_{mEST},$$

(19)

where $\bar{R}_j$ the mean return of stock j is over the estimation period, and $\bar{R}_{mEST}$ is the mean market return over the estimation period.

2.4.2 Market Model with GARCH (1, 1)[11]

Methodological work on prediction models could enhance our understanding of how to best use information about events to test economic hypotheses about firm behavior. The parameters of the market model are estimated using an OLS regression. Under general conditions, OLS is a consistent estimation procedure for the market-model parameters. However, certain assumptions must be met; one of these assumptions is that the coefficients of the market model are constant over time given that R_t is an independent multivariate normally distributed—only then is OLS efficient. This has been questioned by Iqbal and Dheeriya (1991), who employed a random coefficient regression model allowing betas to vary over time. Another assumption is the homoscedasticity of the OLS residuals, that is, their distribution has a constant variance. The main problem here is that the residuals do not have constant variance. Event study methodology models pool data from a number of different companies and periods, and constrains the effects of an event on mean returns to be equal across companies. According to Boehmer et al., (1991,p265), who suggest that" this type of heteroscedasticity in a traditional regression framework can be handled by normalizing the data—that is, by dividing all the observations on each company or event by the standard deviation of observations across that company or event, prior to the estimation by OLS, or by dividing each observation not by the whole-event sample standard deviation, but by the standard deviation within the relevant inside-event window to which the observation belongs".

Ali andGiaccotto (1982) have shown that the standard tests to measure the effect of a specific event on security prices must be adjusted to take into account the presence of heteroscedasticity. Akgiray (1989), and Corhay and Rad (1994), show that the empirical characteristics of return series can be described by GARCH models, developed by Bollerslev (1986, 1987), that allow for non-linear inter-temporal dependence in the residual series. Bera, Bubnys, and Park (1988) show the market-model

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[11] I used E-GARCH- results not reported here- the model did not produce significant different results from the GARCH model.

estimates under ARCH (autoregressive conditional heteroscedasticity) processes are more efficient, and Diebold, Im, and Lee (1988) observed that residuals obtained using the standard market model exhibit strong ARCH properties. The market model corrected for GARCH is

$$\epsilon_{jt}|\varphi_{t-1} \sim (0, h_{jt}),$$

where

$$\epsilon_{jt} = R_{jt} - \alpha_j \beta_{\ jt} R_{mt},$$

(20)

$$h_{jt} = \omega_j + \delta_j h_{jt-1} + \gamma_j \epsilon_{jt-1}^2,$$

(21)

where $\omega_j > 0, \gamma_j > 0, \delta_j \geq 0$, and $\gamma_j + \delta_j < 1$, and ϵ_{it} is the shock to returns on day t of event j, and h_{jt} is the time-varying variance of returns. The GARCH equation makes the variance on day t conditional on the variance of the previous day (h_{jt-1}) and the most recent squared shock $(\epsilon_{jt-1})^2$ in a steady state, with the squared shock set to its expected value (h_{jt-1}), and the variance constant over time, so that $h_{j-1} = h_{jt} = h_j$, the unconditional variance of event i is

$$h_j = \frac{\omega_{jt}}{1-\delta_{2j}-\gamma_{2j}}.$$

(22)

Even though GARCH models with conditional normal distribution allow unconditional error distribution to be leptokurtic, they might not fully explain the high level of kurtosis observed in the distribution of the returns series. Several leptokurtic conditional distribution have been applied in the literature (Baillie and Bollerslev, 1989, and Hsieh (1989), and it is generally accepted that the $t-$ distribution performs better. In conditional heteroscedastic models, the stability condition of the variance process requires that the sum of the estimated parameter, which measures the persistence of the volatility of firm, be less than one. If this sum is equal to one, the process becomes an integrated GARCH (Engle, 1982, 1983, Bollerslev, 1986, and Engle and Bollerslev et al., 1994). Such an integrated process implies the persistence of a forecast of the conditional variance over all future horizons and an infinite variance of the unconditional distribution of ε_{it}. I estimated the market model using E-GARCH where:

$$Log\ h_{jt} = \omega_j + \delta_j Log\ h_{jt-1} + \gamma_j |Z_{jt-1}^2| + \phi_j Z_{jt-1},$$

(23)

where $Z_{jt} = {\epsilon_{jt}}/{\sqrt{h_{jt}}}$.

All parameters in both models are estimated using the maximum likelihood. I will report only the market model estimated by GARCH, unless there is a difference when using E-GARCH; in that case, I will report both.

2.4.3 Market-adjusted Returns Model[12]

MAR (market-adjusted returns model) is computed by subtracting the observed return on the market index for day t R_{mt}, from the rate of return of the common stock of the j^{th} firm on day t:

$$A_{jt} = R_{jt} - R_{mt}. \quad (24)$$

Once we make the adjustments, then we follow the exact same procedure described in the market model to calculate the abnormal and cumulative abnormal returns.

2.4.4 Comparisons Period Mean-adjusted Returns[13]

CP (comparisons period mean-adjusted returns) are computed by subtracting the arithmetic mean return of the common stock of the j^{th} firm computed over the estimation period, $\overline{R_j}$. Once we make the adjustments, then we follow the exact same procedure described in the market model to calculate the abnormal and cumulative abnormal returns.

2.5 CHAPTER SCOPE AND DATA

This chapter aims at answering the question does the selection of different benchmarks or different estimation procedures affect the sign and the significance of the post-listing abnormal returns. As such, this chapter focused on forming portfolios based on certain characteristics and using benchmarks that are appropriate for those characteristics, which I called the characteristic index–based analysis. In addition, this chapter focused on forming portfolios based on the market index and using different benchmarks that are suitable for such analysis, which I called the market index–based analysis. Further, this chapter focused on changing the estimation procedures to determine if that will change the sign and the significance of the post-listing abnormal returns, and to find the method that is a better fit when using daily returns data. In other words, which estimation procedure will provide the least contradictory results for the analysis undertaken? The chapter provided a comprehensive analysis and comparison between the characteristic index and the market index as well as comparisons between different estimation procedures. The sample and data are the same ones I used in the previous chapter; however, in this chapter I used data from the Fama-French website to collect the daily returns on the various market and characteristic index portfolios used in this chapter. Moreover, I used the published data for sentiment from Baker et al., (2006).

2.6 EMPIRICAL RESULTS—THE CHARACTERISTICS INDEX

I built on the base results found in the first chapter when I used the market model as an estimation procedure and the DJIA as the benchmark index. I showed companies that cross-list in a host market while that market is "positive" and achieve significant negative post-listing abnormal returns are timing the

[12] See appendix A.3. Results from that method are not shown, because it is not superior to the GARCH method.
[13] See appendix A.4. Results from that method are not shown, because it is not superior to the GARCH method.

market and the post-market anomaly does exist, but it is explained in the context of the host market condition. In addition, I showed that if companies cross-list in a host market while that host market is "negative," and achieve positive post-listing abnormal returns whether significant or not, that those companies did not time the market, or else why would they time a market that is down; moreover, demonstrating that the post-listing anomaly does not exist.

In this chapter, I will report the results after changing both the benchmark index and the estimation procedure. I will report the results for the hypotheses using only four test statistics[14] (due to space considerations) that are widely used in the event study literature. Hereafter, when I refer to the post-listing anomaly exists, it means that post-listing abnormal returns are negative, whether significant or not.

The hypotheses to be tested are:

H_0: Post-listing anomaly exists regardless of benchmark types

H_A: Post-listing anomaly does not exist regardless of benchmark types

The following hypotheses examine the relationship between host market condition, post-listing anomaly, and market timing.

$H1_A$: Companies time the market

$H1_B$: Companies do not time the market

$H1_B$: Companies do or do not time the market (inconclusive)

The following hypotheses re-examine the relationship between host market condition, post-listing anomaly, and market timing when using different benchmarks and estimation procedures:

$H2_A$: Different benchmarks and different estimation procedures produce the same results

$H2_B$: Different benchmarks and different estimation procedures produce different results

The analysis will concentrated on two states of nature. First, when the host market is a positive, and second, when the host market is a negative. For both, I will focus on the cases where the CAAR is moving in the opposite direction[15] to the host market condition. I want to focus on how the change in benchmarks and estimation procedures affect the sign and the significance of the post-listing abnormal returns. I will compare the OLS market-model estimation procedure with the other estimation procedures, such as Scholes-Williams and GARCH; however, I will only report all three figures if there is a difference between the three procedures. I will report only the OLS and GARCH, regardless of whether there is a difference, in order to confirm the results or to see if there is an effect on the sign and the significance of post-listing abnormal returns. As shown earlier, GARCH dominates other procedures, especially in the case of daily returns. For every estimation procedure, the index returns used for estimation are the same benchmark index used to determine host market index condition, which will insure the consistency of predictions and inferences. I will group the analysis case by case using the benchmark index as a criterion.

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[14] The results from the test statistics are available upon request.

[15] The other state of nature in which CAAR moves directly with host market condition does not exhibit any variation to change.

2.6.1 Low Book-to-market Ratio as the Benchmark

2.6.1.1 Host Market Condition Is a Positive

Table 23 examines the case of using the LOBTM as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of LOBTM. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 23 shows when the host market condition is a positive, based on the average LOBTM portfolio (formed by Fama-French) return over the period (0, +50), the post-listing abnormal return is –24.78%, with significant negative *Z* Patell, ZSTD, TCS, and SCT of –1.877, –3.35, –5.552, and –21.221, respectively. I conclude that forming portfolios based on the characteristic index of LOBTM reproduced the same results shown in chapter one: the post-listing anomaly exists and since the host market condition is a positive, then those companies time the market.

< *Insert Table* 23 >

Table 24 continues the analysis begun in Table 23 but I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 24 shows the post-listing abnormal return is –21.41%, with significant negative TCS, ZST,[16] and SCT of –3.197, –1.731, and –3.429, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 7 depicts how abnormal returns behave during the window of (–50, +50) when using the LOBTM characteristic index benchmark, while the host market condition is a positive and the GARCH estimation procedure is used. Figure 7 shows a pre-listing run-up in price before the listing date, and then a drop in the post-listing abnormal returns over the window of (+11, +50), confirming the hypothesis that those companies time the market.

< *Insert Table* 24 >

< *Insert* Figure 7 >

2.6.1.2 Host Market Condition Is a Negative

Table 25 continues with the same LOBTM characteristic index, but the host market condition is a negative. Based on the average LOBTM portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is –1.03%, with insignificant negative *Z* Patell, ZSTD, TCS, and SCT of 0.500, 0.524, –0161, and –0.161, respectively. Based on the results using OLS, I conclude whether those companies do or do not time the market is inconclusive.

< *Insert Table* 25 >

Table 26 continues the analysis begun in Table 25, but the estimation procedure is changed from OLS to GARCH. Table 26 shows the post-listing abnormal return is 4.46%, with insignificant positive TCS of 1.253, and significant positive ZST and SCT of 1.323 and 1.419, respectively. Based on the results using

[16] Generalized Z test

GARCH, I conclude those companies do not time the market, because why would they time a market that is negative. Moreover, those companies achieved positive significant post-listing abnormal returns, lending support to the hypothesis that the post-listing anomaly does not exist. In addition, I conclude that changing the estimation procedure changes the sign and the significance of post-listing abnormal returns, and GARCH is a better fit, since I used the Scholes-Williams[17] method estimation procedure, and it produced the same results as reported using the GARCH method. Figure 8 depicts how abnormal returns behave during the window of (–50, +50) when using the LOBTM characteristic index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 8 shows a pre-listing run-up in price before the listing date and then a steady positive post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that the post-listing anomaly does not exist, that those companies do not time the market, and changing the estimation procedure changes the sign and the significance of the post-listing abnormal returns.

$< Insert\ Table\ 26 >$

$< Insert$ Figure 8 $>$

2.6.2 High Book-to-market Ratio as the Benchmark

2.6.2.1 Host Market Condition Is a Positive

Table 27 examines the case using HIBTM as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of HIBTM. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 27 shows when the host market condition is a positive, based on the average HIBTM portfolio (formed by Fama-French) return over the period (0, +50), the post-listing abnormal return is –23.43%, with significant negative *Z* Patell, ZSTD, TCS, and SCT of –1.717, –3.982, –8.705, and –14.572, respectively. I conclude that forming portfolios based on the characteristic index of HIBTM reproduced the results shown in chapter one: the post-listing anomaly exists and since the host market condition is a positive, then those companies time the market.

$< Insert\ Table\ 27 >$

Table 28 continues the analysis begun in Table 27, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 28 shows the post-listing abnormal return is –19.90%, with significant negative TCS, ZST, and SCT of –5.012, –1.692, and –4.836, respectively). I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns.

Figure 9 depicts how abnormal returns behave during the window of (–50, +50) when using the HIBTM characteristic index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 9 shows a pre-listing run-up in price before the listing date, and then a

[17] Not reported here, as it produces the same result as the GARCH method

drop in the post-listing abnormal returns over the window of (+11, +50) confirming the hypothesis that those companies time the market.

$< Insert\ Table\ 28 >$

$< Insert$ Figure 9 $>$

2.6.2.2 Host Market Condition Is a Negative

Table 29 continues with the same HIBTM characteristic index, but in this case, the host market condition is a negative, based on the average HIBTM portfolio (formed by Fama-French) returns over the period (0, +50). Table 29 shows the post-listing abnormal return is –1.56%, with insignificant negative *Z* Patell of –0.069, and significant negative ZSTD, and TCS of –4.363, –1.805, and insignificant negative ZST of –1.162. Based on the results using OLS, I conclude that those companies do not time the market.

$< Insert\ Table\ 29 >$

Table 30 continues the analysis begun in Table 29, but in this case, I changed the estimation procedure from OLS to GARCH. Table 30 shows the post-listing abnormal return is 2.84%, with significant positive TCS of 9.543 and significant positive ZST of 1.659. Based on the results using GARCH, I conclude that those companies do not time the market, because why time a market that is negative; moreover, those companies achieved positive significant post-listing abnormal returns, supporting the hypothesis that the post-listing anomaly does not exist. I conclude that changing the estimation procedure changes the sign and the significance of post-listing abnormal returns and GARCH is a better fit, as I used the Scholes-Williams method of estimating the market-model parameters, and it produced the same results as reported when using the GARCH method.

Figure 10 depicts how abnormal returns behave during the window of (–50, +50) when using the HIBTM characteristic index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 10 shows a pre-listing run-up in price before the listing date, and then steady, positive post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that the post-listing anomaly does not exist, that those companies do not time the market, and changing the estimation procedure changes the sign and the significance of the post-listing abnormal returns.

$< Insert\ Table\ 30 >$

$< Insert$ **Figure 10** $>$

2.6.3 The Size Benchmark Index

2.6.3.1 Host Market Condition Is a Positive

Table 31 examines the case of using size (percentile 1% to 50% in terms of ME) as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of small companies. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 31 shows when the host market condition is a positive, based on the average size portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is –23.28%, with significant negative *Z* Patell, ZSTD, TCS, and SCT of –1.738, –3.676, –1.459, and –18.58, respectively). I conclude that forming portfolios based on the characteristic index of small ME reproduced the same results shown in chapter one: the post-listing anomaly exists, and since the host market condition is a positive, then those companies time the market.

< *Insert Table* 31 >

Table 35 produces the same line of analysis as Table 31, except in Table 35, I used big companies (percentile 51% and above) as the benchmark index to determine the host market condition. I conclude that forming portfolios based on the characteristic index of big ME still produces the same results shown in chapter one, which is the post-listing anomaly exists, and since the host market condition is a positive, then those companies time the market.

< *Insert Table* 35 >

Table 32 continues the analysis begun in Table 31, however, in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 32 shows the post-listing abnormal return is –20.60%, with significant negative TCS, ZST, and SCT of –3.786, –1.757, and –6.205, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 11 depicts how abnormal returns behave during the window of (–50, +50) when using the size characteristic index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 11 shows a pre-listing run-up in price before the listing date, and then a drop in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies time the market.

< *Insert Table* 32 >

< *Insert* **Figure 11** >

Table 36 produces the same line of analysis as Table 32 except in Table 36, I used large companies as the benchmark index to determine the host market condition and for estimating the abnormal returns using GARCH. I conclude that changing the estimation procedure from OLS to GARCH in the case of big companies did not change the sign or the significance for the post-listing abnormal returns. Figure 13 produces the same depiction as Figure 11 does, except that in Figure 13, I used big companies as the benchmark index. Figure 13 shows a pre-listing run-up in price before the listing date, and then a drop in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies time the market.

< *Insert Table* 36 >

< *Insert* **Figure 13** >

2.6.3.2 Host Market Condition Is a Negative

Table 33 continues with the same size characteristic index, but in this case, the host market condition is a negative, based on the average size portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is 0.42%, with insignificant positive *Z* Patell, ZSTD, and TCS of 0.568, 0.657, 0.077, respectively. Based on the results using OLS, I conclude that those companies do not time the market.

$< Insert\ Table\ 33 >$

Table 37 produces the same line of analysis as Table 33, except in Table 37, I used big companies as the benchmark index to determine the host market condition. I conclude that those companies do not time the market.

$< Insert\ Table\ 37 >$

Table 34 continues the analysis begun in Table 33, but in this case, I changed the estimation procedure from OLS to GARCH. Table 34 shows the post-listing abnormal return is 6.59%, with significant positive TCS of 2.021, and significant positive ZST of 1.843. Based on the results using GARCH, I conclude that those companies do not time the market, because why time a market that is negative; moreover, those companies achieved positive significant post-listing abnormal returns, which lends support to the hypothesis that the post-listing anomaly does not exist.

I conclude also that changing the estimation procedure changes the significance of post-listing abnormal returns and GARCH is a better fit, since I used the Scholes-Williams method of estimating the market-model parameters, and it produced the same results as reported when using the GARCH method. Figure 12 depicts how abnormal returns behave during the window of (–50, +50) when using the size characteristic index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 12 shows a pre-listing run-up in price before the listing date, and then a steady positive post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that the post-listing anomaly does not exist, that those companies do not time the market, and changing the estimation procedure changed the significance of the post-listing abnormal returns.

$< Insert\ Table\ 34 >$

$< Insert$ Figure 12 $>$

Table 38 produces the same line of analysis as Table 34 except in Table 38, I used the big companies as the benchmark index to determine the host market condition and for estimating the abnormal returns using GARCH. However, the results from Table 38 based on GARCH estimation method are the same results obtained using the OLS estimation method. I conclude that for big companies, changing the estimation procedure did not change the sign or the significance of the post-listing abnormal returns. Figure 14 produces the same depiction as Figure 12 does, except that in Figure 14, I used big companies as the benchmark index. Figure 14 shows a pre-listing run-up in price before the listing date, and then steady, positive post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that the post-listing anomaly does not exist, that those companies do not time the market, and changing the estimation procedure did not change the sign or the significance of the post-listing abnormal returns.

2.6.4 The Small Size and Low Book-to-Market Ratio Benchmark[18]

2.6.4.1 Host Market Condition Is a Positive

Table 39 examines the case of using the small size and LOBTM as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of small size and LOBTM. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 39 shows when the host market condition is a positive, based on the average of using the small size and LOBTM as the market portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is 16.52%, with significant positive *Z* Patell, and ZSTD, TCS, and SCT of 2.959, 2.246, 2.637, and 2.706, respectively. I conclude that forming portfolios based on the characteristic index of size and LOBTM reproduced the same results shown in chapter one; that is, the post-listing anomaly does not exist, and since the host market condition is a positive, then whether those companies are timing the market is inconclusive.

< *Insert Table* 39 >

Table 40 continues the analysis begun in Table 39, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 40 shows the post-listing abnormal return is 17.44%, with significant positive TCS and ZST of 2.456 and 2.702, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 15 depicts how abnormal returns behave during the window of (–50, +50) when using the size-LOBTM characteristic index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 15 shows no pre-listing run-up in price before the listing date, and then an increase in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that whether those companies are timing the market is inconclusive, since they could simply be earning good returns based on their own merit, regardless of whether or not the market is up.

< *Insert Table* 40 >

< *Insert* Figure 15 >

2.6.4.2 Host Market Condition Is a Negative

Table 41 continue with the same small size and LOBTM characteristic index, but in this case, the host market condition is a negative, based on the average size-LOBTM portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is

[18] Other variations occur that I did not report due to space limitations, and no additional inferences can be drawn from the other variations, such as big-low or small-high, etc.

−24.73, with significant negative ZSTD, TCS, and SCT of −4.200, −8.21, and 1.357, respectively. Based on the results using OLS, I conclude that those companies do not time the market.

$< Insert\ Table\ 41 >$

Table 42 continues the analysis begun in Table 41, but in this case, I changed the estimation procedure from OLS to GARCH. Table 42 shows the post-listing abnormal return is −18.456%, with significant negative TCS and ZST of −4.997 and −1.425, respectively). Based on the results using GARCH, I conclude that those companies do not time the market, because why time a market that is negative.

I conclude also that changing the estimation procedure changes the significance of post-listing abnormal returns and GARCH is a better fit, since I used the Scholes-Williams method of estimating the market-model parameters, and it produced the same results as reported when using the GARCH method. Figure 16 depicts how abnormal returns behave during the window of (−50, +50) when using the size characteristic index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 16 shows a pre-listing run-up in price before the listing date, and then a drop in price in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that the post-listing anomaly exists, and that those companies do not time the market.

$< Insert\ Table\ 42 >$

$< Insert$ Figure 16 $>$

2.6.5 Portfolios Formed on Prior Beliefs

Portfolios formed on prior beliefs refer to portfolios based on either STR or LTR. I classified those portfolios as characteristics indices, because I will use the characteristic of either STR or LTR to form the portfolios. I will form portfolios only on negative STR or negative LTR, because in either case, I anticipate a reversal in the future[19] concerning whether the host market is positive or negative.

2.6.5.1 Host Market Condition Is a Positive

Table 43 examines the case of using the portfolios formed on negative LTR as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of negative LTR. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 43 shows when the host market condition is a positive, based on the average negative LTR portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is 15.21%, with significant positive *Z* Patell, ZSTD, TCS, and generalized *Z* sign of 2.655, 2.240, 2.804, and 2.6241, respectively. I conclude that forming portfolios based on the characteristic index of negative LTR reproduced the same results shown in chapter one; that is, the post-listing anomaly does not exist, and since the host market condition is positive, those companies timing the market is inconclusive.

$< Insert\ Table\ 43 >$

[19] See the complete description of the method in the hypothesis development section.

Table 44 continues the analysis begun in Table 43, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 44 shows the post-listing abnormal return is 17.95%, with significant positive TCS of 3.040. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 17 depicts how abnormal returns behave during the window of (–50, +50) when using the negative LTR as the characteristic index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 17 shows a pre-listing run-up in price before the listing date, and then a continued rise in prices, and hence an increase in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that whether those companies are timing the market is inconclusive.

$< Insert\ Table\ 44 >$

$< Insert$ Figure 17 $>$

Table 45 examines the case of using the portfolios formed on negative STR as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of STR. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 45 shows when the host market condition is a positive, based on the average negative STR portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is –41.74%, with significant negative *Z* Patell, ZSTD, and TCS of –1.631, –15.873, and –5.613, respectively. I conclude that forming portfolios based on the characteristic index of negative STR reproduced the same results shown in chapter one; that is, the post-listing anomaly exists and since the host market condition is a positive, those companies time the market.

$< Ins$ert Table 45 $>$

Table 46 continues the analysis begun in Table 45, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 46 shows the post-listing abnormal return is –35.32%, with significant negative TCS and ZST of –10.563 and 2.651, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 18 depicts how abnormal returns behave during the window of (–50, +50) when using the negative STR as the characteristic index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 18 shows a drop in the pre-listing prices before the listing date, which contradicts previous literature that there will be always a run-up in price before the listing date, and then a continued decrease in prices; hence, a decrease in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that whether those companies are timing the market is inconclusive.

$< Insert\ Table\ 46 >$

$< Insert$ Figure 18 $>$

2.6.5.2 Host Market Condition Is a Negative

Table 47 examines the case of using the portfolios formed on negative LTR as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of negative LTR. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 47 shows when the host market condition is a negative, based on the average negative LTR portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is 11.67%, with significant positive ZSTD, TCS, and generalized *Z* sign of 5.641, 1.819, and 1.845, respectively. I conclude that forming portfolios based on the characteristic index of negative LTR reproduced the same results shown in chapter one, which is the post-listing anomaly does not exist, and since the host market condition is a negative, those companies do not time the market.

$< Insert\ Table$ 47 $>$

Table 48 continues the analysis begun in Table 47, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 48 shows the post-listing abnormal return is 14.89%, with significant positive TCS of 2.438. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 19 depicts how abnormal returns behave during the window of (–50, +50) when using the negative LTR as the characteristic index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 19 shows a pre-listing run-up in price before the listing date, and then a continued rise in prices, and hence an increase in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies do not time the market.

$< Insert\ Table$ 48 $>$

$< Insert$ Figure 19 $>$

Table 49 examines the case of using the portfolios formed on negative STR as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of STR. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 49 shows when the host market condition is a negative, based on the average negative STR portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is –31.42%, with significant negative *Z* Patell, ZSTD, and TCS of –1.739, –1.310, and –1.645, respectively. I conclude that forming portfolios based on the characteristic index of negative STR reproduced the same results shown in chapter one; that is, the post-listing anomaly exists and since the host market condition is a negative, those companies timing the market is inconclusive.

$< Insert\ Table$ 49 $>$

Table 50 continues the analysis begun in Table 49, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 49 shows the post-listing abnormal return is –26.55%, with significant negative generalized *Z* sign of –1.409. I conclude that changing the estimation procedure from OLS to

GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 20 depicts how abnormal returns behave during the window of (–50, +50) when using the negative STR as the characteristic index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 20 shows a drop in the pre-listing prices before the listing date, which contradicts previous literature that there will be always a run-up in price before the listing date, and then a continued decrease in prices, and hence a decrease in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that whether those companies are timing the market is inconclusive.

$< Insert\ Table\ 50 >$

$< Insert$ Figure 20 $>$

2.6.6 Portfolios Formed on Momentum

I form portfolios on the characteristic that when those portfolios have a positive mean return from the period –251 to –20 prior to listing, then according to the literature,[20] they should experience positive momentum. Therefore, they should achieve positive average abnormal returns especially after cross-listing, whether or not the host market is positive.

2.6.6.1 Host Market Condition Is a Positive

Table 51 examines the case of using the portfolios formed on positive momentum as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of positive momentum. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 51 shows when the host market condition is a positive, based on the average positive momentum portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is –42.96%, with significant negative *Z* Patell, ZSTD, TCS, and generalized Z sign of –3.915, –1.787, –1.746, and –1.989, respectively. I conclude that forming portfolios based on the characteristic index of positive momentum reproduced the same results shown in chapter one; that is, the post-listing anomaly exists, and since the host market condition is a positive, those companies time the market.

$< Insert\ Table\ 51 >$

Table 52 continues the analysis begun in Table 51, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 46 shows the post-listing abnormal return is –42.48%, with significant negative TCS and ZST of –1.680 and –2.091, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 21 depicts how abnormal returns behave during the window of (–50, +50) when using the positive momentum as the characteristic index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 21 shows a drop in price in the pre-listing period and

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[20] See the hypothesis development section for more discussion on this subject.

negative post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies time the market.

< *Insert Table* 52 >

< *Insert* Figure 21 >

2.6.6.2 Host Market Condition Is a Negative

Table 53 examines the case of using the portfolios formed on positive momentum as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of positive momentum. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 53 shows when the host market condition is a negative, based on the average positive momentum portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is –61.71%, with significant negative *Z* Patell, ZSTD, and TCS of –2.668, –5.576, and –2.164, respectively. I conclude that forming portfolios based on the characteristic index of positive momentum reproduced the same results shown in chapter one; that is, the post-listing anomaly exists, and since the host market condition is a negative, those companies do not time the market.

< *Insert Table* 53 >

Table 54 continues the analysis begun in Table 53, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 54 shows the post-listing abnormal return is –47.98%, with significant negative TCS and generalized *Z* of –2.607, and –1.310, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 22 depicts how abnormal returns behave during the window of (–50, +50) when using positive momentum as the characteristic index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 22 shows a drop in price in the pre-listing period, which contradicts previous literature assertions that there will be always a run-up in price in the pre-listing period, and continuing drop in prices, and hence negative post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies do not time the market.

< *Insert Table* 54 >

< *Insert* Figure 22 >

2.7 EMPIRICAL RESULTS—THE MARKET INDEX

2.7.1 Portfolios Formed on Sentiment

2.7.1.1 Host Market Condition Is a Positive

Table 55 examines the case of using the portfolios formed on sentiment index as the benchmark and as a market index, since I formed portfolios on the market sentiment index. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 55 shows when the host market condition is a positive, based on the average positive sentiment index portfolio (formed by Baker and Wurgler) returns over the period (0, +50), the post-listing abnormal return is –39.66%, with significant negative *Z* Patell, ZSTD, TCS, and SCT sign of –2.999,–1.392, –1.300, and –1.813, respectively. I conclude that forming portfolios based on the market index of positive sentiment reproduced the same results shown in chapter one; that is, the post-listing anomaly exists, and since the host market condition is a positive, those companies time the market.

< *Insert Table* 55 >

Table 56 continues the analysis begun in Table 55, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 56 shows the post-listing abnormal return is –40.87%, with significant negative TCS and generalized *Z* of –1.358 and –1.707, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 23 depicts how abnormal returns behave during the window of (–50, +50) when using the positive sentiment index as the market index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 23 shows a drop in price in the pre-listing period and negative post-listing abnormal returns over the window of (+11 +50), which confirms the hypothesis that those companies time the market.

< *Insert Table* 56 >

< *Insert* **Figure** 24 >

2.7.1.2 Host Market Condition Is a Negative

Table 57 examines the case of using the portfolios formed on a negative sentiment index as the benchmark and as a market index, since I formed portfolios on the negative sentiment market index. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 57 shows when the host market condition is a negative, based on the average market index sentiment portfolio (formed by Baker and Wurgler) returns over the period (0, +50), the post-listing abnormal return is 18.97%, with significant positive *Z* Patell, ZSTD, and TCS of 3.403, 3.001, and 2.764, respectively. I conclude that forming portfolios based on the market index of negative sentiment reproduced the same results shown in chapter one; that is, the post-listing anomaly does not exist, and since the host market condition is a negative, those companies do not time the market.

< *Insert Table* 57 >

Table 58 continues the analysis begun in Table 57, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 58 shows the post-listing abnormal return is 17.88%, with significant positive TCS and generalized *Z* of 2.967 and 1.792, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 25 depicts how abnormal returns behave during the window of (–50, +50) when using positive sentiment as the market index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 25 show the price is almost steady in the pre-listing period, which contradicts previous literature assertions that there will be always a run-up in price in the pre-listing period, and spike increases in prices, and hence positive post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies do not time the market.

$< Insert\ Table\ 58 >$

$< Insert$ Figure 25 $>$

2.7.2 Portfolios Formed on Momentum

The reason this is a market index instead of a characteristic index is I did not form portfolios based on momentum but used the average momentum portfolio returns in the post-listing period to determine the host market condition, then investigated the post-listing abnormal returns.

2.7.2.1 Host Market Condition Is a Positive

Table 59 examines the case of using the portfolios formed on momentum index as the benchmark and as a market index, since I formed portfolios on the market momentum index. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 59 shows when the host market condition is a positive, based on the average positive momentum index portfolio (formed by Fama and French) returns over the period (0, +50), the post-listing abnormal return is –41.83%, with significant negative *Z* Patell, ZSTD, TCS, and SCT sign of –4.088, –2.075, –2.079, and –3.59, respectively. I conclude that forming portfolios based on the market index of positive momentum reproduced the same results shown in chapter one; that is, the post-listing anomaly exists, and since the host market condition is a positive, those companies time the market.

$< Insert\ Table\ 59 >$

Table 60 continues the analysis begun in Table 59, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 60 shows the post-listing abnormal return is –41.28%, with significant negative TCS, and generalized *Z* of –1.995 and –2.278, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 26 depicts how abnormal returns behave during the window of (–50, +50) when using the positive momentum index as the market index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 26 shows a drop in price in the pre-listing period and negative post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies time the market.

$< Insert\ Table\ 60 >$

$< Insert$ Figure 26 $>$

2.7.2.2 Host Market Condition Is a Negative

Table 61 examines the case of using the portfolios formed on positive momentum as the benchmark and as a characteristic index, since I formed portfolios on the characteristic of positive momentum. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 61 shows when the host market condition is a negative, based on the average positive momentum portfolio (formed by Fama-French) returns over the period (0, +50), the post-listing abnormal return is 11.22%, with significant positive *Z* Patell, ZSTD, TCS, and generalized *Z* sign of 2.338, 2.471, 2.612, and 2.262, respectively. I conclude that forming portfolios based on the characteristic index of positive momentum reproduced the same results shown in chapter one; that is, the post-listing anomaly does not exist, and since the host market condition is a negative, those companies do not time the market.

$< Insert\ Table\ 61 >$

Table 62 continues the analysis begun in Table 61, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 62 shows the post-listing abnormal return is 10.56%, with significant positive TCS and generalized *Z* of 2.574 and 2.285, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 27 depicts how abnormal returns behave during the window of (–50, +50) when using positive momentum as the characteristic index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 27 shows a drop in price in the pre-listing period, which contradicts previous literature assertions there will be always a run-up in price in the pre-listing period, and then a rise in prices, and hence an increase in the post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies do not time the market.

$< Insert\ Table\ 62 >$

$< Insert$ Figure 27 $>$

2.7.3 Portfolios Formed on Reversals

The reason this is a market index instead of a characteristic index is I did not form portfolios based on LTR or STR, but I used the average LTR or average STR portfolio returns in the post-listing period to determine the host market condition and then investigated the post-listing abnormal returns.

2.7.3.1 Host Market Condition Is a Positive

Table 63 examines the case of using the portfolios formed on the LTR index as the benchmark and as a market index, since I formed portfolios on the market LTR index. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 63 shows when the host market condition is a positive, based on the average positive LTR index portfolio (formed by Fama and French) returns over the period (0, +50), the post-listing abnormal return is –45.61%, with significant negative Z Patell, ZSTD, TCS, and generalized Z sign of –2.767, –2.281, –1.503, and –1.305, respectively). I conclude that forming portfolios based on the market index of positive LTR reproduced the same results shown in chapter one; that is, the post-listing anomaly exists, and since the host market condition is a positive, those companies time the market.

$< Insert\ Table\ 63 >$

Table 64 continues the analysis begun in Table 63, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 64 shows the post-listing abnormal return is –44.73%, with significant negative TCS and generalized Z of –1.536 and –1.310, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 28 depicts how abnormal returns behave during the window of (–50, +50) when using the positive LTR index as the market index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 28 shows a drop in price in the pre-listing period and negative post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies time the market.

$< Insert\ Table\ 64 >$

$< Insert$ Figure 28 $>$

Table 65 examines the case of using the portfolios formed on the STR index as the benchmark and as a market index, since I formed portfolios on the market STR index. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 65 shows when the host market condition is a positive, based on the average positive STR index portfolio (formed by Fama and French) returns over the period (0, +50), the post-listing abnormal return is –29.19%, with significant negative Z Patell, ZSTD, TCS, and generalized Z sign of –2.063, –9.447, –3.704, and –1.804, respectively. I conclude that forming portfolios based on the market index of positive STR reproduced the same results shown in chapter one; that is, the post-listing anomaly exists, and since the host market condition is a positive, those companies time the market.

$< Insert\ Table\ 65 >$

Table 66 continues the analysis begun in Table 65, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 66 shows the post-listing abnormal return is –25.89%, with significant negative TCS, and generalized Z of –4.592 and –1.821, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 29 depicts how abnormal returns behave during the window of (–50, +50) when using the positive STR index as the market index benchmark, while the host market condition is a positive, and the GARCH estimation procedure is used. Figure 29 shows a steady price in the pre-listing period and a modest run-up in price just before the listing date, and a sharp drop in price and negative post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies time the market.

< *Insert Table* 66 >

< *Insert* Figure 29 >

2.7.3.2 Host Market Condition Is a Negative

Table 67 examines the case of using the portfolios formed on LTR index as the benchmark and as a market index, since I formed portfolios on the market LTR index. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 67 shows when the host market condition is a negative, based on the average negative LTR index portfolio (formed by Fama and French) returns over the period (0, +50), the post-listing abnormal return is 4.88%, with significant positive *Z* Patell, ZSTD, and generalized *Z* sign of 1.540, 1.975, and 1.881, respectively. I conclude that forming portfolios based on the market index of negative LTR reproduced the same results shown in chapter one; that is, the post-listing anomaly does not exist, and since the host market condition is a negative, those companies do not time the market.

< *Insert Table* 67 >

Table 68 continues the analysis begun in Table 67, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 68 shows the post-listing abnormal return is 6.44%, with significant positive TCS and generalized *Z* of 1.392 and 2.300, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 30 depicts how abnormal returns behave during the window of (–50, +50) when using the negative LTR index as the market index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. Figure 30 shows a steady rise in price in the pre-listing period and positive post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies do not time the market.

< *I*nsert Table 68 >

< *Insert* Figure 30 >

Table 69 examines the case of using the portfolios formed on STR index as the benchmark and as a market index, since I formed portfolios on the market STR index. In this table, I use the OLS estimation procedure to estimate the market-model parameters and calculate the post-listing abnormal returns. Table 69 shows when the host market condition is a negative, based on the average negative STR index portfolio (formed by Fama and French) returns over the period (0, +50), the post-listing abnormal return is 16.24%, with significant positive *Z* Patell, ZSTD, and TCS of 1.559, 2.017, and 1.791, respectively. I conclude that forming portfolios based on the market index of negative STR reproduced the same results shown in chapter one; that is, the post-listing anomaly does not exist, and since the host market condition is a negative, those companies do not time the market.

< *Insert Table* 69 >

Table 70 continues the analysis begun in Table 69, but in this case, I use the GARCH estimation technique to estimate the parameters of the market model and from that, I estimate the abnormal returns in the post-listing period. Table 70 shows the post-listing abnormal return is 19.00%, with significant positive TCS, and generalized Z of 1.887 and 1.926, respectively. I conclude that changing the estimation procedure from OLS to GARCH did not change the sign or the significance for the post-listing abnormal returns. Figure 31 depicts how abnormal returns behave during the window of (–50, +50) when using the negative STR index as the market index benchmark, while the host market condition is a negative, and the GARCH estimation procedure is used. The figure shows a run-up in prices just before the listing date and a continuing increase in prices and positive post-listing abnormal returns over the window of (+11, +50), which confirms the hypothesis that those companies do not time the market.

$< Insert\ Table\ 70 >$

$< Insert$ Figure 31 $>$

2.8 SUMMARY AND CONCLUDING REMARKS

The simple answer to the question raised at the beginning of the chapter "does the selection of benchmark and estimation procedure matter" is "yes," the selection of the benchmark and the estimation procedures matters in some cases. This chapter confirms previous research that finds a pre-listing run-up in price, and hence an increase in pre-listing returns and that on or around the cross-listing date, positive returns are observed. The evidence also confirms the results from chapter one that the host market condition plays a significant role in explaining the post-listing anomaly, and some companies time the market before cross-listing. In addition, this chapter reveals some cases in which no pre-run-up in prices before listing occurs, and in other cases, a drop in prices takes place before cross-listing.

Therefore, if the host market condition as indicated by the choice of the benchmark index is important in determining the calculation, the estimation, and the interpretation of the post-listing abnormal returns, then it follows, if I change the selection of the benchmark index and the estimation procedures that are used to calculate and estimate the post-listing abnormal returns, then the question is will I obtain different results? If that were the case, then, it follows that researchers must choose the correct benchmark index and correct estimation procedures or else the interpretation of their results will be inaccurate. The evidence reveals that, on the one hand, for some of the different characteristic index benchmarks used, different estimation procedures changed the sign and the significance of the post-listing abnormal returns. On the other hand, for all the different market index benchmarks used, different estimation procedures did not change the sign or the significance of the post-listing abnormal returns. I conclude that the characteristic index benchmark is a better fit when forming portfolios based on certain characteristics. Moreover, I conclude that the GARCH model is superior in estimating the market-model parameters, more so than any other method, because when there is a conflict between results using GARCH and OLS, I use the Scholes-Williams method of estimation, and I found that results from GARCH are the same as those from Scholes-Williams.

Overall, choosing the right benchmark index for analysis is important in event studies that investigate post-listing abnormal returns, especially since event studies are based on grouping companies on certain characteristics, which in many cases does not reflect the overall market average. For every characteristic index benchmark used there will a different set of companies that correspond to that characteristic index, and hence, the sign, the significance, and in turn, the interpretation of the post-listing abnormal returns will vary. I believe for those reasons previous research was not able to explain the post-listing anomaly, because using an inaccurate benchmark index will produce conflicting results.

This chapter raises numerous research questions, such as is there any evidence of earnings management for companies that time the market; is there an increase in a company's value in terms of Tobin's-Q when the companies cross-list, especially if those companies time the market; does the market overreact to cross-listing; what are the main drivers for CAAR, and many others. I will address some of those questions in the next chapter.

CHAPTER 3
MARKET TIMING AND EARNINGS MANAGEMENT

3.1 INTRODUCTION

Adam Smith (1937) writes that due to the separation between ownership and control there will be always negligence in the management of the affairs of such companies. Jensen (1986) argues that if left unmonitored, entrenched managers may waste free cash flows. Dittmar and Mahrt-Smith (2007) find that the value of a dollar of cash is substantially less if a firm has poor corporate governance. Teoh et al. (1998b) report that companies that report high earnings usually do so by adopting discretionary accounting accrual. Lang, Lins, and Miller (2003) find that firms' cross-listing on U.S. exchanges results in greater analytic coverage and increased market valuations. These benefits of cross-listing are likely to improve if firms time listing to a window of opportunity (period of high earnings) or manage earnings at the cross-listing period. Alford et al. (1993) and Lang et al. (2006) argue that firms are thus likely to manage earnings at the cross-listing period.

In this chapter, I built on the results obtained in the previous chapters. In particular, I formed portfolios that follow my earlier conclusions noting some companies' time the markets, while others do not. The portfolios will be of companies that attain significant negative abnormal returns in the post-listing period of (+11, +50), while the host market condition is a positive based on the average DJIA[21] index for the period (0, +50). In addition, I formed portfolios of firms that attain significant positive abnormal returns in the post-listing period of (+11, +50), while the host market condition is a negative based on the average DJIA index for the period (0, +50). I used the DJIA index as my market index, because most of the companies in those portfolios are compared against that index. I will use the discretionary accruals concept as the tool to evaluate the hypothesis that if firms time the market before they cross-list, they must be engaging in earnings management, and if they do not time the market, then they are not engaging in earnings management. I define that those companies engaging in earnings management have positive and significant discretionary accruals while others not engaging in earnings management have negative discretionary accruals. To conduct the analysis, I created a dummy variable where it is equal to 1 if companies time the market and 0 if they do not. To estimate discretionary accruals, I will use the various models discussed in the literature[22] for doing so; however, I will report only those results that employed the latest models in my analysis.

In previous chapters, I discussed the distribution of daily returns used for the analysis and reported that daily returns do not exhibit normal distributions. This leads to other challenges, such as heteroscedasticity and autocorrelation. To address this, I conducted the analysis with various estimation

[21] I formed portfolios that some companies time the market and some do not based on the various results reached from the previous chapters. I used the DJIA as the benchmark index to estimate and calculate the abnormal returns.
[22] See the literature review for further elaboration on the subject.

techniques to correct for both heteroscedasticity and autocorrelation. In addition, I used parametric and non-parametric tests to prove the validity of the results.

The evidence presented in this chapter finds that companies that time the market achieve significant negative post-listing abnormal returns, and they have significant positive contributions to discretionary accruals; hence, they engage in earnings management. Moreover, companies that do not time the market achieve significant positive abnormal return in the cross-listing period, and they have significant negative contribution to the discretionary accruals, hence they do not engage in earnings management.

This chapter contributes to the literature in various ways. First, not only does it confirm previous chapters' results that some companies do time the market, while others who do not, but also it identifies that those that do are engaging in earnings management. Second, this chapter used a wide variety of discretionary accruals estimation procedures thus confirming that discretionary accruals are a relevant measure in indentifying earnings management. Third, this chapter recommends that the most accurate measure of discretionary accruals is the model described by Ball and Shivakumar (2006). Fourth, this chapter leaves open some research questions, such as what is the effect of market timing on firm valuation in terms of Tobin's-Q over the long run? How do non-market timers compare with market timers in terms of the value of their growth opportunities and profitability? Do analysts' data and forecasting accurately reflect the market-timing decision? Does the market overreact to cross-listing whether the company times the market or not?

3.2 LITERATURE REVIEW

Foreign firms desiring to cross-list on U.S. stock exchanges must have at least US$100 million of market value in public shares to cross-list on the NYSE and US$20 million to cross-list on NASDAQ. The NYSE requires a minimum total pre-tax income of $100 million for the latest three fiscal years and at least US$25 million of pre-tax income in the cross-listing year. Cross-listing on U.S. stock exchanges offers several benefits such more liquidity, lower bid-ask spreads, the ability to raise capital at cheaper prices, an increase in investor recognition, and the diversifying of financial risk. Because cross-listing provides significant economic benefits, managers have incentives to meet the cross-listing threshold of U.S. exchanges, and those incentives increase for firms close to violating market value or earnings thresholds. Biddle and Saudagaran (1992) find that the demanding listing threshold prevents firms from cross-listing on U.S. exchanges. Dechow and Skinner (2000) and Healy and Wahlen (1999) find that firms manage earnings to obtain cheaper capital, to meet analysts' projections, to meet regulatory thresholds, and to increase stock prices.

Ferreira and Matos (2008) find that institutional investors prefer to invest in firms with better corporate governance. Bailey, Karolyi, and Salva (2006) find that firms who list in the United States enjoy high returns. Lang, Lins, and Miller (2003) report that firms that cross-list on U.S. exchanges experience higher valuation.

Harris and Muller (1999) find that the earnings of cross-listed firms are related to their market value. Amir et al. (1993) and Barth and Clinch (1996) find that the earnings reported by cross-listed firms are related to their stock market performance. Lang, Ready, and Yetman (2003) find that cross-listing firms have less aggressive earnings management than non-cross-listing firms in their local home markets. Reese and Weisbach (2001) and Lang et al. (2006) suggest that reporting less transparently creates an opportunity for foreign firms to manage earnings. Frost and Kinney (1996) report that foreign firms are reluctant to comply with the greater transparency for fear that they might reveal aggressive revenue recognition, hidden reserves, or a substantially underfunded pension plan.

Anand et al. (2006) note the main proxy for a firm's earnings quality is thecommon factor identified by factor analysis performed on three measures ofearnings quality commonly reported in the literature: accruals quality, earningsvariability, ând the absolute value of abnormal accruals. Schill et al. (2007) finds that when firms expand assets they experience a period of abnormally low returns, and vice-versa. Fairfield, Whisenant, and Yohn (2003) find that accrual is a general market mispricing of net operating assets growth. Schill et al. (2007) document a strong negative correlation between firm asset growth and subsequent firm abnormal returnsand following Titman, Wei and Xie (2004) show that the asset growth effect is weaker in times of increased corporate oversight, consistent with the idea of earnings management.

Dechow, Sloan, and Sweeney (1996) reports there is strong and robust evidence that the level of accruals is a negative cross-sectional predictor of abnormal stock returns. Desai, Rajgopal, and Venkatachalam (2004), and Pincus, Rajgopal, and Venkatachalam (2007) both document that cash flows is a positive cross-sectional predictor of returns. Ndubizu (2007) reports that cross-listed firms have significant return on assets (*ROA*), cash flows, and working capital accruals,that peak in the listing period and fall in subsequent years. Hence, he concluded that cross-listed firms could be either timing their listings or managing earnings. Smith et al., (1997) find that the stock prices of cross-listed firms rise by 8% at the time of listing on U.S. stock exchanges and deteriorate thereafter. Lee (1991), Damodaran et al. (1993), Lau et al. (1994), and Rothman (1995) report a positive market reaction at the time of cross-listing. Hirshleifer, Hou, Teoh, and Zhang (2004) find that net operating assets scaled by lagged total assets are a strong negative predictor of future stock returns. Hirshleifer et al. (2004) note that inparticular; investors overvalue firms with high net operating assets, and undervalue firms with low net operating assets. DuCharme, Malatesta, and Sefcik (2004) assert that some firms manipulate earnings before stock offerings. Ball and Shivakumar (2006) and Jo and Kim (2007) have producedrecent research suggesting that firms issuing equity can inflate their stock price temporarily via earnings management prior to the offering. Teoh, Welch, and Wong (1998) find that firms report increasing discretionary accruals before seasoned equity offerings and that post-listing performance is negatively related to earnings management.

3.3 HYPOTHESIS DEVELOPMENT

To develop my hypothesis, I started with forming portfolios of companies that exhibit market timing and portfolios of companies that do not. In doing so, I used the same research method employed in Chapter 1. Table 71 shows that some companies cross-list, while the host market condition is a positive (based on the average DJIA index return in the period (0, +50), and yet the result is significant negative abnormal returns after they cross-list, particularly in the period of (+11, +50). Those companies make up the portfolio of market timers[23].

$< Insert\ Table\ 71 >$

Further, according to Table 72, some companies cross-list while the host market condition is a negative (based on the average DJIA index return in the period (0, +50), and yet they achieve significant positive abnormal returns after they cross-list, particularly in the period of (+11, +50). Those companies make up the portfolio of non-market timers.

$< Insert\ Table\ 72 >$

Total accruals are usually defined according to Dechow et al. (1995, p. 203) as the difference between net income ($NI_{i,t}$) and cash flow from operations ($CFO_{i,t}$).

$$TOTACC_{i,t} = NI_{i,t} - CFO_{i,t}. \tag{25}$$

Instead of computing total accruals from net income and cash flow from operations, the result can be found using current accruals ($CURRACC_{i,t}$), proxied by the change in working capital (excluding cash), and non-current accrual ($NONECURRACC_{i,t}$), proxied by depreciation, depletion, and amortization (Dechow et al., 1995, p. 203). In effect, all other accrual items are ignored.

$$TOTACC_{i,t} = CURRACC_{i,t} + NONECURRACC_{i,t}. \tag{26}$$

I used both the first definition (equation 25) and the second definition (equation 26) of total accruals for my model; however, I will report only the results from the first definition (equation 25), since there were no differences in the results when using the second definition. The model of Kang and Sivaramakrishnan (1995, p. 358) predicts the balance sheet levels of accounts represented in current accruals, rather than changes in those accounts, and includes amortization from the income statement, rather than amortization from the cash flow statement. Accrual measures in all models are typically scaled by total assets from the previous year ($TA_{i,t}$).

Dechow et al. (2010), report that tests for earnings management accounting accruals are decomposed into discretionary and non-discretionary accruals. The discretionary accrual is the proxy for earnings management, while the non-discretionary accruals reflect the firm's business activities of accounting accruals. Early research employed the levels or changes in working capital accruals as discretionary accrual proxies (DeAngelo, 1986). Healy (1985) defines discretionary accruals as the change in non-cash working capital:

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[23] I used the Russell 2000 index and it did not provide different results from the DJIA. Please see appendix F.

$DA_{i,t} = (\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STD_{i,t}) / \Delta TA_{i,t}-1$

(27)

where

CA = the change in current assets

CL = the change in current liabilities

CASH = the change in cash

TA = total assets

McNichols (2000) reports that when using those models, the assumption that non-discretionary accruals are constant is not realistic, as the level of non-discretionary accruals changes with the companies' changing business conditions. Jones (1991) developed models to estimate the non-discretionary component of total accruals, enabling total accruals to be decomposed into discretionary or non-discretionary components.

Jones (1991) uses a discretionary accrual proxy similar to that used by Healy (1985) and includes the change in revenues and the level of property, plant, and equipment as additional relevant variables. These two variables are designed to capture non-discretionary accruals that may be present. The Jones and modified-Jones models regress total accruals ($TOTACC_{i,t}$) on change in revenues ($\Delta REV_{i,t}$) and change of gross property, plant and equipment ($\Delta PPE_{i,t}$), deflated by beginning-of-fiscal-year total assets ($TA_{i,t-1}$). The discretionary accruals of the Jones model are measured by the residuals of that regression.

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_0 \frac{1}{TA_{i,t-1}} + \beta_{1t} \frac{\Delta REV_{i,t}}{TA_{i,t-1}} + \beta_{2t} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \varepsilon_{it}.$$

(28)

Dechow, Sloan, and Sweeney (1996) show that the original Jones model has low power in cases in which firms manipulate revenue through the misstatement of net accounts receivable. This is because the original Jones model includes the change in revenue as a control for non-discretionary accruals. Dechow et al. (1995), Kothari et al. (2005), and Ball and Shivakumar (2006) find that the Jones model of non-discretionary accruals is substantially miss-specified. The model ignores the roles of accruals in reducing noise in earnings (Dechow, 1994) and in timely loss recognition. Dechow, Sloan, and Sweeney (1996) report that the modified-Jones model further adjusts changes in receivables ($\Delta REC_{i,t}$) to control for the manipulation of revenues through credit sales. Concerns with such misspecifications led researchers to adopt performance-matching procedures.

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_{0t} \frac{1}{TA_{i,t-1}} + \beta_{1t} \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2t} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \varepsilon_{it}.$$

(29)

Kothari, Leone, and Wasley (2005) propose a procedure that entails differencing estimates of discretionary accruals from Jones-type models for treatment firms and control firms matched on industry and return on assets. However, their results did not generate any significant differences from not using the matching control firms. McNichols (2000) shows models that do not consider long-term earnings growth are particularly prone to misspecification and that accruals are positively related to analysts' forecasts of future growth, even after controlling for growth in the current period.Dechow (1994), Barth et al. (2001), and Dechow and Dichev (2002) suggest that accruals are negatively correlated with concurrent operating cash flows and positively correlated with past and future operating cash flows. However, the Jones and modified-Jones models do not take into account the systematic associations between operating cash flows and accruals. Dechow et al. (1995) find that extant unexpected accrual models are likely to overestimate (underestimate) unexpected accruals of firms with high (low) operating cash flows. Consistent with McNichols' (2002) augmentation of the Jones model with cash flows, Dechow and Dichev (2002) note that since the objective of non-discretionary accruals is to correct temporary matching problems with a firm's underlying cash flows, they should be negatively correlated with contemporaneous cash flows and positively correlated with adjacent cash flows. Therefore, they propose including past, present, and future cash flows (*CF*) as additional relevant variables:

$$TOTACC_{i,t} = \alpha_i + \alpha_{1i} CF_{i,t} + \alpha_{2i} CF_{i,t-1} + \alpha_{3i} CF_{i,t+1}, \quad (30)$$

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_i \frac{1}{TA_{i,t-1}} + \beta_{1i} \frac{\Delta REV_{i,t}}{TA_{i,t-1}} + \beta_{2i} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t} \frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t} \frac{CF_{i,t}}{TA_{i,t-1}} + \delta_{2t} \frac{CF_{i,t+1}}{TA_{i,t-1}} + \varepsilon_{it}, \quad (31)$$

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_i \frac{1}{TA_{i,t-1}} + \beta_{1i} \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t} \frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t} \frac{CF_{i,t}}{TA_{i,t-1}} + \frac{CF_{i,t+1}}{TA_{i,t-1}} + \varepsilon_{it}. \quad (32)$$

Ball et al. (2005), and Ball and Shivakumar, (2006), controlled for the non-linearity of accruals with respect to cash flows using the following piece-wise modifications of the Jones model with cash flows where $DCF_{i,t}$ is an indicator variable equal to one if operating cash flows ($CF_{i,t}$) are negative, and zero otherwise; $D\Delta CF_{i,t}$ is an indicator variable equal to one if operating cash flow changes ($\Delta CF_{i,t}$) are negative, and zero otherwise:

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_i \frac{1}{TA_{i,t-1}} + \beta_{1i} \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t} \frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t} \frac{CF_{i,t}}{TA_{i,t-1}} + \delta_{2t} \frac{CF_{i,t+1}}{TA_{i,t-1}} + \delta_{3t} \frac{DCF_{i,t}}{TA_{i,t-1}} + \delta_{3t} \frac{DCF\, x\, CF_{i,t}}{TA_{i,t-1}} + \varepsilon_{it},$$

(33)

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_i \frac{1}{TA_{i,t-1}} + \beta_{1i} \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t} \frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t} \frac{CF_{i,t}}{TA_{i,t-1}} + \delta_{2t} \frac{CF_{i,t+1}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF_{i,t}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF\, x\, \Delta CF_{i,t}}{TA_{i,t-1}} + \varepsilon_{it}.$$

(34)

Defond and Park (2001) and Allen, Larson, and Sloan (2010) provide a detailed analysis of the time-series properties of accruals. They show that accruals consist of either positively serially correlated accruals (non-discretionary) or negatively serially correlated accruals (discretionary) accruals. Fedyk, Singer, and Sougiannis (2010) show that predictable stock returns following extreme accruals can be explained by subsequent accrual reversals. Baber, Kang, and Li (2010) show how the reversal of discretionary accruals from prior periods constrains earnings management in the current period.

In this chapter, I test whether earnings management is different between cross-listing companies that time the market and cross-listing companies that do not. I will use the model developed by Ball and Shivakumar (2006). In particular, I use equation 34 to estimate total accrual and from which I estimate the discretionary accruals:

H_0: Companies that time the market exhibit earnings management

H_A: Companies that do not time the market do not exhibit earnings management

3.4 RESEARCH METHOD

I created a dummy variable *DTIMERS* that takes the value of 1 when the portfolio of companies refers to market timers and a value of 0 when the portfolio of companies refers to non-market timers. Then, I used the discretionary accrual estimates from equation 34, as this reflects the most recent research on the best way to estimate discretionary accruals. I used an independent sample *t*-test to compare the means of a normally distributed interval dependent variable for two independent groups (market timers and non-market timers). This *t*-test is designed to compare means of the same variable between two groups. In my sample, I compare the mean of absolute discretionary accruals[24] (*ABS_DISCACCR*) of firms that time the market with firms that do not and ideally, these firms are randomly selected from a larger population of firms; however, these firms were selected based on a predetermined criterion regarding the host market condition and the sign and the significance of the post-listing abnormal returns. When I use the *t*-test for comparing independent groups, I also test the hypothesis on equal variance. If I assume that the two samples have the same variance, then the first method, called the pooled variance estimator, is used.

[24] More discussion on this variable is found on the next page.

Otherwise, when the variances are not assumed to be equal, Satterthwaite's method is used. According to Table 73, panel (B), Pr >*F*—this is the two-tailed significance probability—is less than (<0.05), so there is evidence that the variances for the two groups, market timers and non-market timers, are different. Therefore, I will rely on the second method (Satterthwaite's variance estimator). According to Table 73, panel (A), since the *p*-value (0.001)—using the Satterthwaite's method of the difference in means for the variable ABS_DISCACCR between the timers and non-timers groups—is less than the pre-specified alpha level (0.05), then the difference in means is statistically significantly different from zero. Therefore, I conclude that there is a significant difference between the means of the two samples.

$< Insert\ Table\ 73 >$

In addition to using parametric tests, I used non-parametric tests, because the daily returns distribution is not normal, as discussed in Chapter 1. The Wilcoxon-Mann-Whitney test is a non-parametric analog to the independent samples' *t*-test. According to Table 74, panel (B), the results suggest there is a statistically significant difference between the underlying distributions of market timers and the non-market timers ($z = 47.6333, p = 0.0001$). The Mann-Whitney and the equivalent Wilcoxon tests are rank sum tests and not median tests.

$< Insert\ Table\ 74 >$

It is possible, for groups to have different rank sums and yet have equal or nearly equal medians. Therefore, I conducted a difference in median tests between market timers and non-market timers. According to Table 75, panel (B), the results suggest there is a statistically significant difference between the underlying distributions of market timers and the non-market timers ($z = 22.2227, p = 0.0001$).

$< Insert\ Table\ 75 >$

After I established that there is a significant difference in means and medians between the market timers group and non-market timers group, I used (based on the previous literature) a regression model in which the dependent variable is estimated using a two-step method as follows:

First, I estimated the total accruals using the following equation:[25]

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_i \frac{1}{TA_{i,t-1}} + \beta_{1i} \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t} \frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t} \frac{CF_{i,t}}{TA_{i,t-1}} + \delta_{2t} \frac{CF_{i,t+1}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF_{i,t}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF \ x \ \Delta CF_{i,t}}{TA_{i,t-1}} + \varepsilon_{it}.$$

(35)

Then, I used the following equation to estimate the discretionary accruals:

$$DISCACCR_{i,t} = \frac{TOTACC_{i,t}}{TA_{i,t-1}} - \alpha_i \frac{1}{TA_{i,t-1}} + \beta_{1i} \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t} \frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t} \frac{CF_{i,t}}{TA_{i,t-1}} + \delta_{2t} \frac{CF_{i,t+1}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF_{i,t}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF \ x \ \Delta CF_{i,t}}{TA_{i,t-1}}$$

(36)

[25] More discussion on the equation can be found in the section on hypothesis development.

Once I estimated the discretionary accruals, I took the absolute value of that and developed my dependent variable *ABS_DISCACCR*. This estimation method is well-established in the literature as the best measure of discretionary accruals, for it also measures the quality of those accruals.

In addition to the dependent variable estimation and according to the literature[26] I used the following regression model:

$$|DISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + Leverage_{i,t} + BMR_{i,t}$$

where

$|DISCACCR_{i,t}|$ = absolute discretionary accruals

$Dtimers_{i,t}$ = a dummy variable that takes the value of 1 when companies time the market and the value of 0 when companies do not time the market

$ROA_{i,t}$ = a control variable that reflect the returns on assets

$Size_{i,t}$ = a control variable that reflects the size of the companies (is the natural log of total assets)

$Leverage_{i,t}$ = a control variable that is believed to affect company fortune; it measures how the company is financing its assets and is calculated as the total liabilities divided by common equity and retained earnings

$BMR_{i,t}$ = a control variable that measures the ratio of book–to-market ratio

Before I started using the model, I tested for correlation among independent variable by using the Pearson correlation coefficients. These numbers measure the strength and direction of the linear relationship between the variables. Under H_0: *Rho*= 0 that the correlation (*Rho*) is zero. According to Table 76, the *p*-value for all the values is less than the significance level of (0.05), therefore I reject the null hypothesis of no correlation between the variables and conclude that there is indeed correlation between the variables, which may lead to some specification problems or serial autocorrelation. However, it is worth noting that the correlation between the variables is not high, except the correlation between *ROA* and *SIZE*, which is 0.40664.

$< Insert\ Table\ 76 >$

3.5 REGRESSION DIAGNOSTICS AND HYPOTHESIS RESULTS

One of the main assumptions of the OLS regression is the homogeneity of variance of the residuals. A commonly used graphical method is to plot the residuals versus predicted values. Figure 32 shows the pattern of the data points widening toward the right side, which is an indication of mild heteroscedasticity.

$< Insert\ figure\ 32 >$

[26] See the section on previous research and hypothesis development.

I ran diagnostic statistics on my regression model:

$$|DISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + Leverage_{i,t}.$$

According to Table 77, panel (A), the *F* statistic = 3763.77, with a *p*-value < (0.0001), which means the independent variables are not all equal and they are significantly different from zero. The R-Sq and "Adj" R-Sq are both (0.3394), suggesting that the model explains about 34% of the variation in the dependent variable. Table 77, panel (B) shows the parameter estimates and the dummy variable *DTIMERS* is positive and significant at the (0.05) significance level, which suggests that companies that time the market are in fact engaging in earnings management, since they contribute positively to the discretionary accruals; however, further investigation is still warranted.

To check on the degree of multicollinearity, I will use the variance inflation factor (VIF), and a variable whose VIF values are greater than 10 may merit further investigation. I define tolerance as 1/VIF, which is used by many researchers to check on the degree of collinearity, and a tolerance value lower than 0.1 is comparable to a VIF of 10. It means that the variable could be considered as a linear combination of other independent variables. I also exclude the intercept from those calculations, but it is still included in the calculation of the regression. Table 77, panel (B) shows that for all the independent variables, the VIF is less than 2 and tolerance is less than 1, which means we do not have a case of perfect multicollinearity, however, we do have some sort of multicollinearity (there is no way to have zero multicollinearity in any regression).

To investigate further the issue of multicollinearity, I calculate the condition number, which is a commonly used index of the global instability of the regression coefficients—large condition number, 10 or more, is an indication of instability. The output produced in Table 77, panel (C) contains the Eigenvalues of the correlation matrix of the regressors, along with the proportion of variation each regressor explains for the Eigenvalues. The Eigenvalues are ranked from highest to lowest. The extent or severity of the multicollinearity problem is evident by examining the size of the Eigenvalues. As long as no big differences are evident among the Eigenvalues (large variability), then there is no high degree of multicollinearity. Freund and Littell (2000, pp. 100–1) and Myers (1990), report that small Eigenvalues indicate near-perfect linear dependencies or high multicollinearity. According to Table 77, panel (C), the Eigenvalues corresponding to the independent variables are not very small. The square root of the ratio of the largest Eigenvalues to the smallest Eigenvalues is given by the last element in the condition number column. Myers (1990), in general, notes a large condition number indicates a high degree of multicollinearity. The condition numbers for the independent variables are between 1 and 1.9, indicating a very mild case of multicollinearity. In reality, most econometric studies will be impacted by some correlation between the explanatory variables.

The White test tests the null hypothesis that the variance of the residuals is homogenous. According to Table 77, panel (D), since the *p*-value is very small (<0.001), I will reject the hypothesis of homoscedasticity and accept the alternative hypothesis that the variance is not homogenous.

$< Insert\ Table\ 77 >$

Since I rejected the hypothesis of homoscedasticity, then I need to estimate the asymptotic covariance matrix of the estimates under the hypothesis of heteroscedasticity. Panels (B) and (C) in Table 78 show that the point estimates of the coefficients are exactly the same as in ordinary OLS—as shown in Table 78, panel (C)—but the standard errors are calculated based on the asymptotic covariance matrix. Note the changes are in the standard errors and *t*-tests (but no change in the coefficients).

$< Insert\ Table\ 78 >$

The analysis methods presented were based on the assumption that the independent variables are exogenous, that is, the error terms in the linear regression model are uncorrelated or independent of the explanatory variables. Under the exogeneity assumption, the least squares estimator is an unbiased and consistent estimator. Explanatory variables that are not exogenous are called endogenous variables. Under departures from the exogeneity conditions, $\hat{\beta}$ is no longer an unbiased and consistent estimator of β. It turns out that the measurement error in the explanatory variables creates a correlation between the variables and the error term similar to the omitted variable case. As such Wooldridge, (2002), Ashenfelter and Graddy (2003) document that measurement errors in the dependent variable, in general, do not lead to violation of the least squares assumptions, because the measurement error in the dependent variable is simply absorbed in the disturbance term of the model. However, errors in the dependent variable may inflate the standard errors of the least squares estimates. Instrumental variables are an alternative method to obtain unbiased and consistent estimators of β under departures from the exogenous assumption.

Before I start using instrumental variables, however, there are methods to determine if endogeneity is indeed a problem. Since my regression variables include *ROA* and that is a measure of profitability, I suspect that this variable is endogenous, since there are many factors that can affect the *ROA*. The objective here is to determine if the variable *ROA* is endogenous. The first step is to regress *ROA*on a constant and other variables that I will use later as instruments. The residuals (v) from this regression is saved and used as an explanatory variable in the regression of

$$|DISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + Leverage_{i,t} + BMR1_{i,t} + V_{i,t}.$$

If the *t*-statistic corresponding to $V_{i,t}$ is significant, then the null hypothesis is rejected, and I conclude that the variable *ROA* is indeed endogenous. The variables that I will use as instruments are as follows:

GDP = Gross domestic product

Size = Log of total assets

Sent = Sentiment index as calculated by Baker and Wurgler (2002)

Mich = Sentiment index as calculated by the university of Michigan

Country = Refers to country of origin for each firm

Disclose = Refers to the quality of disclosures developed by La Porta et al. (1998)

Antidir = Refers to an index of anti director rights developed by La Porta et al. (1998)

Access = Refers to the degree of information access investors have in each country for each firm

Corrupt = Corruption index for each country developed by La Porta et al. (1998)

Leverage = A control variable that is believed to affect the company fortune, and measures how are the company financing its assets, and is calculated as the total liabilities divided by (common equity and retained earnings)

BMR = A control variable that measures the ratio of book-to-market ratio

According to Table 79, panel (B), the t-statistic of (v) is (32.73) with a p-value of (<0.001); the null hypothesis is rejected, and I conclude that the variable *ROA* is indeed endogenous.

$< Insert\ Table\ 79 >$

After determining that *ROA* is indeed endogenous, I used the instrumental variables method to re-estimate the regression

$$|DISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + Leverage_{i,t} + BMR1_{i,t}\ .$$

According to Table 80, the dummy variable DTIMERS has a t-statistic value of (30.57), with a p-value of (0.001), suggesting that DTIMERS is positive and highly significant, which supports the previous results that firms that time the market engage in market timing, even after using the IV method.

< InsertTable 80 >

3.6 ROBUSTNESS CHECK[27]

3.6.1 Detecting and Correcting for Heteroscedasticity

I established that the data suffer from heteroscedasticity. By definition, heteroscedasticity implies that the variances of the disturbances are not constant across observations. Verbeek (2004) notes there are formal tests for detecting the presence of non-spherical disturbances: White's general test, the Goldfeld-Quand t-test, and the Breusch-Pagan test.

To conduct the analysis first, I define the parameters of the model as Const (for the intercept), C_Timers (*TIMERS*), C_BMR (*BMR*), C_Size (*Size*), C_LEV (*LEV*), C_ROA (*ROA*). I will be regressing *ABS_DISCACRR* against *Timers*, *BMR*, *Size*, *LEV*, and *ROA*. Output reveals according to Table 81, panel (C) that the test-statistic value for White's has a p-value equal to (0.0001). Therefore, I reject the null hypothesis of homoscedastic disturbances. The Breusch–Pagan test yields the same results; hence, I reject the null hypothesis of homoscedastic disturbances. Rejecting the null hypothesis leads to no indication of

[27] I used the Fama-French model to run the regression using different independent variables and it did not produce different results. See appendix G for the results.

what should be done in terms of adjusting for heteroscedasticity, since it offers no insight on the problematic variable.

$< Insert\ Table\ 81 >$

The estimation of the least parameters under heteroscedasticity starts with estimating a robust version of the variance–covariance matrix of the OLS estimator. These robust estimators will then be used to calculate the standard errors of the least squares estimators and to perform hypothesis tests. I will then move to a weighted least squares estimation and an estimate of the parameters using one-step and two-step feasible generalized least squares (FGLS) Here, HCCME is the acronym for heteroscedastic-corrected covariance matrix. As discussed in Greene (2003), it has been argued that in small samples, the White's estimator tends to underestimate the true variance–covariance matrix, resulting in higher *t*-statistic ratios. In other words, using this estimator leads to liberal hypothesis tests involving the least square estimators. Davidson and MacKinnon (1993) offered two alternative versions of this estimator. The HCCME0 option calculates the standard errors based on White's estimator. The HCCME1 option calculates the first alternative suggested by Davidson and MacKinnon. The HCCME2 option calculates the second alternative suggested by Davidson and MacKinnon. The HCCME3 option produces yet another modification of the White's estimator. Please see appendix C for these estimation options.

To calculate the generalized least squares (GLS) estimator, first, I must transform the response variable and then regress it against the transformed explanatory variables. As given in Greene (2003, p. 226) and Verbeek (2004, p. 85), a common approach used to obtain the weights is to specify that the variance of the disturbances is proportional to one of the regressors. I will assume that the variance of the disturbance is proportional to the square of *ROA*. Output reveals according to Table 82, Panel (B) that *DTIMERS* with a *t*-statistic of 2.03 and *p*-value of 0.042 is still positive and significant, and *ROA* with *t*-statistic –27.75 and *p*-value of 0.001 is still negative and significant. As should be expected, the standard errors of the parameters using the square of *ROA* as weights are smaller than the standard errors when not using the weights. The signs of the parameters are the same across both analyses OLS, and weighted least squares (WLS). Comparing the magnitudes of the parameter estimates, one can see that the magnitude of the parameter values for the OLS regression is higher than those using the WLS and the GLS.

$< Insert\ Table\ 82 >$

I have assumed until now that when $\{\varepsilon|X\} = \sigma^2\mho$, where $\mho$ is a positive definite, symmetric matrix, it is known. However, when $\mho$ is assumed to be unknown, the unrestricted heteroscedastic regression model will have too many parameters that need estimation and given the limitations on the sample size, it will be impossible. However, according to Green (2003) and Verbeek (2004, p. 86), by expressing $\sigma^2\mho$ as a function of only a few parameters, for example, the parameter α, and accordingly, the analysis could have more than one variable, making the parameter (α) a vector. The modified variance–covariance matrix can now be denoted as $\mho(\alpha)$. Therefore, estimating $\mho$ is now restricted to estimating(α). Green (2003) and Verbeek (2004) report that there are two ways of doing this. The first method involves the two-step FGLS technique and the second method involves the maximum likelihood estimation. I will use the two-step FGLS estimator.

The analysis results are given in Table 83. I estimated FGLS by applying the same idea I used in the WLS technique, but in this case, the variance of the disturbances is proportional to the expected value of the residual of the vector parameter. Table 83, panel (B) shows the standard errors of the estimates are now higher than the standard errors of the estimates when $1/ROA^2$ weight was used. The signs of the coefficients are the same, which confirms that *DTIMERS* with *t*-statistic of 5.93 and *p*-value of 0.001 is still positive and significant at the 0.05 significance level.

$< Insert\ Table\ 83 >$

As discussed by Enders (2004), in a typical econometric model, the variance of the disturbances is assumed to be stable (constant) over time. However, there are instances when economic time-series data exhibit periods of high "volatility" followed by periods of low "volatility" or "calmness." Greene (2003, p. 238) when the variance of the disturbance at a given time period is assumed to depend on the variance of the disturbance in the previous time periods, then the homoscedastic variance assumption in this case is violated. The disturbance terms in the linear models must therefore take into account the dependence of its variance on past disturbances. This is the basic principle behind Engle's (1982) autoregressive, conditionally heteroscedastic models (ARCH). He proposed a methodology where the variances of the disturbances are allowed to depend on its history. That is, the variance of the series itself is an autoregressive time-series.

The simplest form of Engle's ARCH model is the ARCH (1) model. The main idea behind the model is that the conditional variance of the disturbance at time *t* depends on the squared disturbance term at time *t*–1. Therefore, the conditional variance of the disturbance at time t depends on the past values of the squared disturbances. The unconditional variance on the other hand is constant. To test for ARCH effect the Lagrange Multiplier test (LM) can be used to test for ARCH (q) effects. The hypothesis tested is under the null hypothesis; there are ARCH effects and the alternative hypothesis that there are no ARCH effects. Table 84, panel (A) show the values for *SSE* and *MSE*, which are for the error and mean sums of squares, respectively. The *MSE* is really the unconditional variance of the series. The Durbin-Watson statistic is used to test for serial correlation and will be discussed in detail later. *DFE* is simply the degrees of freedom and is the total number of observations – 1. The values of AIC (Akaike information criterion) and BIC are information criterion values that are used to assess model fit. Smaller values of the statistics are desirable. Table 84, panel (B) contains the Q and LM tests. Both statistics test for heteroscedasticity in the time-series. The Q statistic proposed by McLeod and Li (1983) and checks for changing variability over time. The test is highly significant across the 12 lag windows. The LM statistic is also highly significant across all 12 lag windows indicating that a higher order ARCH process needs to be used to model the data.

$< Insert\ Table\ 84 >$

Bollerslev (1986) extended the ARCH models where the variance of the disturbance at time t depends on its own lag as well as the lag of the squared disturbances so he extended the ARCH process by allowing an autoregressive moving average process for the error variance. The resulting formulation is referred to as the generalized autoregressive conditional heteroscedastic model or GARCH. Both the ARCH and the GARCH models forecast the variance of the disturbance at time t. The ARCH models use the weighted averages of the past values of the squared disturbances, while the GARCH model use the weighted average of the past values of both the squared disturbances and the variances. The basic principle is to make the forecast of the variance at time t more accurate.

Baltagi (2008, p. 370) the LM test can also be used for testing GARCH effects. In a test for a GARCH (p,q) model, however, the hypothesis tested is the null of an ARCH(q) process versus an ARCH(p+q) process here, the LM test is based on the regression of the test statistic, which is the same as before. Greene (2003, p. 239, pp. 242–43) (GARCH) reports that the MLE can be used to estimate the parameters of both the ARCH and GARCH models. The GARCH process introduces the lagged values of the variances. The analysis results are given in Table 85, panel (B) indicates that there is strong evidence of GARCH effects (p-value < 0.0001). The normality test is highly significant (p-value < 0.0001), which indicates that the residuals from the GARCH model are not normally distributed—a clear contradiction to the normality assumption. ARCH0 gives the estimate of α_0, ARCH1 gives the estimate of α_1, and GARCH1 gives the estimate of β_1.

$$< Insert\ Table\ 85 >$$

Having established the presence of ARCH and GARCH and the need for higher order ARCH process to model the data then I used ARCH (7) and GARCH (2) process. The output in Table 86, panel (B) shows that starting from ARCH (4) the t-statistic is (1.40) with a p-value of (0.1601), which renders ARCH (4) insignificant. Moreover, GARCH (1) with a t-statistic of (0.69) with a p-value of (0.491) renders GARCH (1) insignificant. the parameters estimates show the *DTIMERS* with a t-statistic of (2,424.23) and with a p-value of (<.0001) is highly positive and significant, which supports that the companies that time the market engage in earnings management as the *DTIMERS* coefficient is positive and significant.

$$< Insert\ Table\ 86 >$$

3.6.2 Detecting and Correcting for Autocorrelation and Heteroscedasticity

Autocorrelation in regression models often occurs when models are miss-specified or when variables are mistakenly omitted from the model. In the omitted variable case, unobserved or omitted variables that are correlated over time are now absorbed in the error term, causing autocorrelation. In addition, if the assumption that the disturbance related to an observation is independent of the disturbance related to another observation, in that case this situation is called serial correlation or autocorrelation. Autocorrelation also implies that the errors are heteroscedastic (Greene, 2003, p. 258). OLS estimators, although unbiased, will be inefficient and will have incorrect standard errors. Estimation techniques under the assumption of serial correlation parallel the estimation methods for heteroscedasticity. That is, an estimate of the variance–covariance matrix is needed. Using the variance and covariance, the matrix of the disturbances can be constructed, and the GLS estimator can be calculated using the Prais-Winsten transformations. However, the traditional approach for the transformation is done by using the Cochrane and Orcutt (1949) method in which they dropped the first observation for computational ease. Verbeek (2004, p. 100) finds deleting the observation leads to an approximate GLS estimator that is not as efficient as the GLS estimator obtained by including all the observations. Greene (2003) extends the process to the second-order autocorrelation process, which can become very complex as the order of the autoregressive process increases.

To detect autocorrelation, the Durbin-Watson test is perhaps the most commonly used test, testing the null hypothesis of no autocorrelation. The LM test suggested by Breusch and Godfrey (1978) is an alternative to the Durbin-Watson test. The test statistic has a chi-squared distribution with p degrees of freedom. The output in Table 87, panel (B) reveals that the *DW* statistic of 0.0092 with Pr <.0001 for Pr<*DW*, which is highly significant for testing positive serial autocorrelation, and with Pr <1.0000 for Pr >*DW*, which is insignificant for negative serial autocorrelation. The LM test with a p-value of <0.0001 indicates that the significance extends to the higher order autoregressive process.

$< Insert\ Table\ 87 >$

Having detected the presence of autocorrelation, I will estimate the parameters by using either GLS or FGLS. The first step is to determine the degree of the autoregressive process so I ran a back-step regression starting with 5lags and then the back-step regression model eliminates the lags that have an insignificant t-statistic. Table 88, panel (A) reports an estimate of the first five order autocorrelations and as it shows, they are all significant. Notice again that the null hypothesis of no autocorrelation is rejected. Panel (B) reports the results of the back-step regression model where lag 3, 4, and 5 has a t-statistic of 1.42, 0.64, and 0.02 with a p-value of 0.1558, 0.9826, and 0.5214, respectively, and they are all insignificant. The results imply that the autoregressive model should be of an order 2 or 3

$< Insert\ Table\ 88 >$

The next step is to re-estimate the model while adjusting for both autocorrelations using an AR order of 3 and adjusting for heteroscedasticity using the GARCH method of an order ($q = 6$). The FGLS estimates are then reported, assuming the AR3 model, and GARCH ($q = 6$) with no intercept. Using the FGLS method to estimate the regression, Table 89, panel (B) reports the parameter estimates without an intercept and document that *DTIMERS* has a t-statistic of 41.44 with a p-value of <0.0001, which is highly significant. Also notice that the R-Sq reported in Table 89, panel (A) is 0.56, which is higher than what was reported in Table 83, panel (A) of 0.2768, because the R-Sq is redefined, for the fact that there is no intercept.

$< Insert\ Table\ 89 >$

Table 90, panel (C) shows the final estimate of the model after using AR3 and GARCH ($q = 6$) and reports that *DTIMERS* has a t-statistic of 308.6 with a p-value of <0.0001, which is highly positive and significant, and confirms that companies that time the market engage in earnings management. Panel (C) also reports that AR3 with a p-value of 0.0636 is insignificant at the 0.05 level and that ARCH (5) and ARCH (6) are both insignificant with a p-value of (1.000).

< Insert Table 90 >

3.7 SUMMARY AND CONCLUDING REMARKS

The literature cites many reasons why companies cross-list, such as lowering the cost of capital, increasing investor recognition, and taking advantage of real growth opportunities. Based on the evidence cited in this chapter, I found that some companies cross-list in a host market, while that host market is up, whereas other companies cross-list regardless of market conditions.

Examining the evidence reveals that using a market index to condition for the host market condition and using the same market index to estimate the abnormal returns, some companies that cross-list while the market is up achieve significant negative abnormal returns, while others who cross-list while the market is down achieve significant positive abnormal returns. I attributed that variation to market timing; that is, if the companies that cross-list while the market is up and achieve significant negative abnormal returns, then those companies are timing the market, while others who cross-list while the market is down do not time the market.

Further, this chapter focused on discovering any further evidence that can prove some companies do time the market. The discretionary accruals research reports if companies have a high degree of discretionary accruals, then those companies engage in earnings management. I built a dummy variable *DTIMERS* that takes the value of 1 if the companies time the market and 0 if they do not. I ran multiple regression models on an independent variable that is discretionary accruals using the most up to date research to confirm my analysis.

The study used a wide variety of parametric and non-parametric tests and a diagnostic regression analysis adjusting for heteroscedasticity and autocorrelation. The evidence shows the companies that time the market have a positive and significant contribution to discretionary accruals, which means that those companies engage in earnings management and that may explain why those companies achieve significant negative abnormal returns after they cross-list.

This study makes a valuable contribution to the literature by highlighting the relationship between the cross-listing decision and the host market condition, post-listing abnormal returns, and the relation to earnings management. Researchers of cross-listing must take into consideration all those factors, investors must not buy shares of cross-listing companies without conducting due diligence, and financial analysts must not issue a recommendation to buy a firm that cross-lists unless they have examined the timing of cross-listing and if there is any sign of earnings management involved.

This study leaves open opportunity for additional research to answer questions such as: does cross-listing create value for market timers or non-market timers, and does the market generally overreact to cross-listing, regardless of whether the company times the market or not.

4. CONCLUSION

The cross-listing literature collaboratively reported that after companies cross-list, this results in negative post-listing returns. The literature calls this phenomenon the post-listing anomaly. This study approached the anomaly of post-listing returns from a new perspective. That perspective questioned the idea that post-listing abnormal returns are in fact anomalies. To demonstrate that perspective, this study developed a link between companies' motives for cross-listing and the post-listing abnormal returns. It is common knowledge that identifying the motives for each company is overly burdensome; thus, I resorted to a simple idea, the host market condition. Therefore, it serves as the common motivating factor linking cross-listing, and post-listing abnormal returns is the host market condition. I choose an index (either a market index or a characteristic index can be used) to use as a benchmark against which to compare a portfolio of companies. If that benchmark index's average returns during the period of (0, +50) are positive, then the host market index is positive and vice versa.

To make the connection to companies motives, I hypothesize that if companies cross-list for genuine performance consideration, they will achieve either significant positive or insignificant post-listing abnormal returns, regardless of the market condition. If they cross-list for any other reasons, they will achieve significant negative abnormal returns. Further, if companies cross-list in a host market while that host market is positive and yet achieve significant negative post-listing abnormal returns, then they must be market timers, and if they list in a host market while that host market is negative and they achieve significant positive post-listing abnormal returns, then they are not market timers.

The evidence reveals that that the post-listing anomaly can be explained in the context of a host market condition, such as if the host market condition is negative, then that offers a reason why post-listing abnormal returns are negative. If it is positive and cross-listed companies achieve negative post-listing abnormal returns, then those companies are timing the market.

In addition, the study used a wide variety of market index benchmarks and characteristic index benchmarks to verify that the results were not reached by an incorrect use of the appropriate benchmark. The study reports that the characteristic index benchmark is a better fit when using event study methodology, as this is usually done by grouping companies based on certain characteristics. Moreover, the study suggests using the GARCH estimation procedure as the method for estimating and calculating the abnormal returns, because the statistical characteristics of daily returns and GARCH produce the same results as the Scholes-Williams method whenever there is a disagreement with the OLS method. The evidence also confirms that post-listing abnormal returns can be explained in the context of the host market condition and there are some companies that time the market, while others do not.

Finally, this study investigated the idea of market timing in relation to earnings management. As such, if some companies time the market to cross-list, they must be trying to achieve as high a return as possible (in that case pre-listing returns); thus, it is more than likely that those companies engage in earnings management. I ran a regression where the independent variable is absolute discretionary accruals and a dummy variable that takes the value of 1 if the companies time the market and 0 otherwise. This reveals companies that time the market have significant positive parameter estimates in the regression, which further supports the idea that market timers engage in earnings management, and that is why they achieve significant negative abnormal returns after cross-listing.

This study leaves open the possibility for further research. Do the companies that time the market—compared with those that do not—create value for their shareholders in the long run? Or do they not? This study contributes to the literature by guiding those pursuing cross-listing research concerning post-listing returns toward using the correct benchmark, estimation procedure, company grouping based on certain characteristics, analyzing those companies based on their cross-listing timing, and studying whether they are engaging in any sort of accounting manipulations.

REFERENCES

Agrawal, A., J. F. Jaffe, and G. N. Mandelker. 1992. The post-merger performance of acquiring firms: A re-examination of an anomaly. *Journal of Finance* 47:1605–21.

Ahren, K. 2009. Sample selection and event study estimation. *Journal of Empirical Finance*16(3):466–82.

Akgiray, V. 1989. Conditional heteroscedasticity in time-series of stock returns: Evidence and forecasts. *Journal of Business* 62:55–80.

Alexander, G. J., C. S. Eun, and S. Janakiramanan. 1987. Asset pricing and dual listing on foreign capital markets: A note. *Journal of Finance* 42(1):151–58.

Alexander, G. J., C. S. Eun, and S. Janakiramanan. 1988. International listings and stock returns: Some empirical evidence. *Journal of Financial and Quantitative Analysis* 23(2):135–51.

Allen, E. J., C. R. Larson, and R. G. Sloan. 2010. Accrual reversals, earnings and stockreturns. Working paper, University of California at Berkeley and WashingtonUniversity in St. Louis.

Alford, A., J. Jones, R. Leftwich, and M. Zmijewski. 1993. The relative informativeness of accounting disclosures in different countries. *Journal of Accounting Research* 31:183–223.

Ali, M. M., and C. Giaccotto. 1984. A study of several new and existing tests for heteroscedasticity in the general linear model, *Journal of Econometrics* 26:355–74.

Amir, E., T. Harris, and E. Venuti. 1993. A comparison of the value-relevance of U.S. vs. non-U.S. GAAP accounting measures using form 20-F reconciliation. *Journal of Accounting Research* 31:230–64.

Ammer, J. M., S. B. Holland, D. C. Smith, and F. E. Warnock. 2005. Look at ME now: What attracts U.S. shareholders? Board of Governors of the Federal Reserve System International Finance Discussion Paper no. 815; EFA 2004 Maastricht no. 4086; AFA 2006 Boston Meetings Paper.

Anand, A., F. Milne, and L. Purda. 2006. Voluntary adoption of corporate governance mechanisms. Working paper no. 1112. Queen's Economics Department. Available at http://ssrn.com/abstract=921450.

Aretz, K., S. M. Bartram, and P. F. Pope. 2007. Macroeconomic risks and characteristic-based factor models. *Journal of Banking and Finance* 34(6):1383–99.

Ashenfelter, O., and K. Graddy. 2003. Auctions and the price of art. *Journal of Economic Literature* 41:763–87.

Baber, W. R., S. Kang, and Y. Li. 2010.Discretionary accrual reversal and the balance sheet as an earnings management constraint.Working paper.Georgetown University and the George Washington University.

Bailey, W., G. A. Karolyi, and C. Salva. 2006. The economic consequences of increased disclosure: Evidence from international cross-listings. *Journal of Financial Economics* 81(1):175–213.

Baillie, R. T., and T. Bollerslev. 1989. Common trends in a system of exchange rates. *Journal of Finance* 44:167–81.

Baker, K. H., and R. B Edelman. 1990. OTC Market switching ad stock returns: Some empirical evidence. *Journal of Financial Research* 13:325–38.

Baker, H. K., and R. B. Edelman. 1992. AMEX-to-NYSE transfers, market microstructure, and shareholder wealth, *Financial Management* 21:60–72.

Baker, H. K., W. A. Khan, and R. B. Edelman. 1994. The post-dual listing anomaly. *Journal of Economics and Business* 46(4):287–97.

Baker, M., R. Talliaferro, and J. Wurgler. 2006. Predicting returns with managerial decision variables: Is there a large-sample bias? *Journal of Finance*.1645-1680.

Baker, M., and J. Wurgler. 2000. The equity share in new issues and aggregate stock returns. *Journal of Finance* 55:2219–57.

Baker, M., and J. Wurgler. 2002. Market timing and capital structure. *Journal of Finance* 57:1–32.

Baker, M. P., and J. C. Stein. 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets* 7(3):271–99.

Baker, M. P., and J. A. Wurgler. 2007. Investor sentiment in the stock market. Available at SSRN: http://ssrn.com/abstract=962706.

Bakke, T.-E., and T. M. Whited. 2007, 2006. Which firms follow the market? An analysis of corporate investment decisions.AFA Chicago Meetings Paper. Available at SSRN: http://ssrn.com/abstract=891570.

Ball, R., and P. Brown. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6:159–78.

Ball, R., S. Kothari, and J. Shanken. 1995. Problems in measuring portfolio performance: an application to contrarian investment strategies. *Journal of Financial Economics* 38:79−107.

Ball, R., A. Robin, and G. Sadka. 2008. Is financial reporting shaped by equity markets or by debt markets? An international study of timeliness and conservatism.*Review of Accounting Studies* 13:168–205.

Ball, R., and L. Shivakumar. 2006. Role of accruals in asymmetrically timely gain and loss recognition. *Journal of Accounting Research* 44(2):207–42.

Baltagi, B.2008.*Econometric Analysis of Panel Data.* 4th ed.Chichester: Wiley.

Banz, R. W. 1981. The relationship between return and market value of common stocks.*Journal of Financial Economics* 9:3–18.

Barber, B., and J. Lyon. 1997. Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics* 43:341–72.

Barth, M., and G. Clinch. 1996. International accounting differences and their relation to share prices: Evidence from UK, Australian, and Canadian firms. *Contemporary Accounting Research* 13:135–70.

Barth, M. E., D. P. Cram, and K. K. Nelson. 2001. Accruals and the prediction of future cash flows. *Accounting Review* 76:27–58.

Bar-Yosef, S., and L. D. Brown. 1977. A re-examination of stock splits using moving betas. *Journal of Finance* 32:1069–80.

Basu, S. 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the EMH. *Journal of Finance* 32(3):663–682.

Basu, S. 1983. The relationship between earnings' yield, market value, and return for NYSE common stocks: Further evidence. *Journal of Financial Economics* 12:129–56.

Beaver, W. 1968. The information content of annual earnings announcements. *Journal of Accounting Research Supplement* 6:67–92.

Bekaert, G., R. H. Campbell, and C. Lundblad. 2001. Emerging equity markets and economic development. *Journal of Development Economics* 66:465–64.

Bekaert, G., R. H. Campbell, and R. L. Lumsdaine. 2002. The dynamics of emerging market equity flows. *Journal of International Money and Finance* 21:295–350.

Bera, A., E. Bubnys, and H. Park. 1988. Conditional heteroscedasticity in the market model and efficient estimates of betas. *Financial Review* 23:201–14.

Bhandari, L. C. 1988. Debt/equity ratio and expected common stock returns: Empirical evidence. *Journal of Finance* 43:507–28.

Biddle, G., and S. Saudagaran. 1992. Foreign stock listing: Benefits, costs, and the accounting policy dilemma. *Accounting Horizons* 5:69–80.

Billingsley, P. 1979. *Probability and measure.*New York: Wiley.

Blattberg, R. C., and N. J. Gonedes. 1974. A comparison of the stable and student distributions as statistical models for stock prices. *Journal of Business* 47:244–80.

Boehmer, E., J. Musumeci, and A. Poulsen. 1991. Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics* 30:253–72.

Bollerslev, T. 1986. Generalised autoregressive conditional heteroskedasticity.*Journal of Econometrics* 51:307–27.

Bollerslev, T. 1987. A conditional heteroskedastic time series model for speculative prices and rates of return. *Review of Economics and Statistics* 69:542–47.

Bollerslev, T., R. F. Engle, and D. B. Nelson. 1994. ARCH models.In *Handbook of econometrics*, Vol. 4, R. F. Engle and D. McFadden, eds. Amsterdam: North-Holland, 2959–3038.

Breeden, D. T., M. R. Gibbons, and R. H. Litzenberger. 1989. Empirical tests of the consumption-based CAPM. *Journal of Finance* 44(2):231–63.

Breen, W. J., and R. Banz. 1986. Sample-dependent results using accounting and market data: Some evidence. *Journal of Finance* 41:779–93.

Breusch, T. S., and A. R. Pagan. 1979. A simple test for heteroscedasticity and random coefficient variation. *Econometrica* 47:1287–94.

Bris, A., S. Cantale, and G. P. Nishiotis. 2007. *European Financial Management* 13(3):498.

Brown, S. J., W. N. Goetzmann, and S. A. Ross. 1995. Survival. *Journal of Finance* 50(3):853–73.

Brown, S. J., and J. B. Warner. 1980. Measuring security price performance. *Journal of Financial Economics* 8(3):205–58.

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

Burns, N., and S. Kedia. 2006. The impact of performance -based compensation on misreporting. *Journal of Financial Economics* 79:35–67.

Camerer, C. F. 1995. Individual decision making.In *Handbook of experimental economics,* A. E. Roth and J. H. Kagel, eds.Princeton, NJ: Princeton University Press, 587–703.

Camerer, C. F. 1998. Can asset markets be manipulated? A field experiment with racetrack betting. Journal of Political Economy 106 (*3*): 457-482.

Cantale, S. 1996. The choice of a foreign market as a signal.Working paper.Tulane University.

Carhart, M. M. 1997. On persistence in mutual fund performance.*Journal of Finance* 52(1):57–82.

Chan, K. C., N. Jegadeesh, and J. Lakonishok, J. *1996*. Momentum strategies.*Journal of Finance* 51:1681–1713.

Chan, K. C., N. F. Chen, and D. A. Hsieh. 1985. An explanatory investigation of the firm size effect. *Journal of Financial Economics* 14:451–71.

Chan, L. K. C., Y. Hamao, and J. Lakonishok. 1991. Fundamentals and stock returns in Japan. *Journal of Finance* 46:1739–64.

Chan, L. K. C., N. Jegadeesh, and J. Lakonishok. 1995. Momentum strategies. Working paper series, vol. w5375.NBER. Available at SSRN: http://ssrn.com/abstract=225438.

Charitou, A., C. Louca, and S. Panayides. 2007. Cross-listing, bonding hypothesis and corporate governance. *Journal of Business Finance and Accounting* 34(7–8):1281–1306.

Chen, H., M. Y. Hu, and J. C. P. Shieh. 1991. The wealth effect of international joint ventures: The case of U.S. investment in China. *Financial Management* 20(4):31–41.

Chen, N. F. 1991. Financial investment opportunities and the macro-economy.*Journal of Finance* 46(2):529–54.

Chen, N. F., R. Roll, and S. Ross. 1986. Economic forces and the stock market. *Journal of Business* 59:383–403.

Chen, Q., I. Goldstein, and W. Jiang. 2007. Price informativeness and investment sensitivity to stock price. *Review of Financial Studies* 20:619–50.

Chopra, N., J. Lakonishok, and J. Ritter. 1992. Measuring abnormal performance: Do stocks overreact? *Journal of Financial Economics* 31:235–68.

Cochrane, D., and G. H. Orcutt. 1949. Application of least squares regression to relationships containing autocorrelated error terms. *Journal of the American Statistical Association* 44:32–61.

Cochrane, J. H. 2001. *Asset pricing*.Princeton, NJ: PrincetonUniversity Press.

Coffee, J. 1999. The future as history: The prospects for global convergence in corporate governance and its implications. *Northwestern University Law Review* 93:641–708.

Coffee, J. 2002. Racing towards the top? The impact of cross-listings and stock market competition on international corporate governance.*Columbia Law Review* 102:1757–1831.

Cohen, R. B., P. A. Gompers, and T. Vuolteenaho. 2002. Who under reacts to cash flow news? Evidence from trading between individuals and institutions.Special issue on limits to arbitrage.*Journal of Financial Economics* 66(2–3):409–62. (Formerly NBER working paper 8793.)

Collins, D., M. Rozeff, and W. Slatka. 1982. The SEC's rejection of SFAS no. 19: Tests of market price reversal. *Accounting Review*:1–17.

Collins, D. W., and W. T. Dent. 1979. The proposed elimination of full cost accounting in the extractive petroleum industry: An empirical assessment of market consequences. *Journal of Accounting and Economics*1(1):3–44.

Collins, D. W., and W. T. Dent. 1984. A comparison of alternative methodologies used in capital market research. *Journal of Accounting Research* 22(1):48–84.

Cooper, M. J., H. Gulen, and M. J. Schill. 2007. Asset growth and the cross section of stock returns. *Journal of Finance* 63(4):1609–1651.

Copeland, T. E., and D. Mayers. 1982. The value line enigma (1965–1978): A case study of performance evaluation issues. *Journal of Financial Economics* 10:289–321.

Corhay, A., and A. T. Rad. 1994. Statistical properties of daily returns: Evidence from European stock markets. *Journal of Business Finance and Accounting* 21:271–82.

Corrado, C. 1989. A non-parametric test for abnormal security price performance in event studies.*Journal of Financial Economics* 23:385–95.

Cowan, A. R. 1992. Non-parametric event study tests.*Review of Quantitative Finance and Accounting* 2:343–58.

Cowan, A. R. 1993. Tests for cumulative abnormal returns over long periods: Simulation evidence. *International Review of Financial Analysis* 2(1):51–68.

Cowan, A. R. 2007. *Eventus 8.0 user's guide, standard edition 2.1.* Ames, IA: Cowan Research LC.

Cowan, A. R., N. Nayar, and A. K. Singh. 1990. Stock returns before and aftercalls of convertible bonds. *Journal of Financial and Quantitative Analysis* 25:549–54.

Cusatis, P., J. Miles, and J. Woolridge. 1993. Restructuring through spin-offs: The stock market evidence. *Journal of Financial Economics* 33:293–311.

Da, Z., and P. Gao. 2005. Default risk and equity return: Macro effect or micro noise? Available at SSRN: http://ssrn.com/abstract=659241.

Damodaran, A., C. Liu, and W. Van Harlow. 1993. The effects of international dual listings on stock price behavior. Working paper.New York University.

Daniel, K., D. Hirshleifer, and A. Sunbrhamanyam. 1988. Investor psychology and security market under and overreactions. *Journal of Finance* 53:1839–86.

Daniel, K., and S. Titman. 2004. Market reactions to tangible and intangible information. Working paper.Northwestern University and University of Texas.

Dann, L. 1981. Common stock repurchase: An analysis of returns to bondholders and stockholders. *Journal of Financial Economics* 9(1981):113–138.

Davidson, R., and J. G. MacKinnon. 1993. *Estimation and inference in econometrics*. New York: OxfordUniversity Press.

DeAngelo, L. 1986. Accounting numbers as market valuation substitutes: A study of management buyouts of public stockholders. *Accounting Review* 61(3):400–20.

DeBondt, W., and R. Thaler. 1985. Does the stock market overreact? *Journal of Finance* 40:793–805.

DeBondt, W., and R. Thaler. 1987. Further evidence on investor over-reaction and stock market seasonality. *Journal of Finance* 42:557–81.

Dechow, P., and D. Skinner. 2000. Earnings management: Reconciling the views of accounting academics, practitioners, and regulators. *Accounting Horizons* 14(2):235–50.

Dechow, P., and I. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *Accounting Review* 77:35–59.

Dechow, P. M. 1994. Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals.*Journal of Accounting and Economics*18(1994):3–42.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1995. Detecting earnings management. *Accounting Review* 70:193–225.

Dechow, P. M., W. Ge, C. R. Larson, and R. G. Sloan. 2010. Predicting material accounting misstatements. *Contemporary Accounting Research.*AAA 2008 Financial Accounting and Reporting Section (FARS) Paper. Available at SSRN: http://ssrn.com/abstract=997483.

Dechow, P. M., R. G. Sloan, and A. Sweeney. 1996. Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC. *Contemporary Accounting Research* 13:1–36.

Defond, M. L., and C. W. Park. 2001. The reversal of abnormal accruals and the market valuation of earnings surprises. *Accounting Review* 76(3):375–404.

Desai, H., S. Rajgopal, and M. Venkatachalam. 2004. Value-glamour and accruals mispricing: One anomaly or two? *Accounting Review* 79:355–85.

Desai, H., and P. C. Jain. 1997. Long-run common stock returns following stock splits and reverse splits. *Journal of Business* 70(3). Available at SSRN: http://ssrn.com/abstract=8448.

Desai, M. A., Dyck, I. J. Alexander, and L. Zingales. Theft and Taxes (December 2004). CEPR Discussion Paper No. 4816. Available at SSRN: http://ssrn.com/abstract=700662.

Dharan, B. G., and D. L. Ikenberry. 1995. The long-run negative drift of post-listing stock returns. *Journal of Finance* 50(5):1547–74.

Diebold, F. X., J. Im, and J. Lee. 1988. *Conditional heteroscedasticity in the market.*Finance and Economics Discussion Series, 42, Division of Research and Statistics, Federal Reserve Board, Washington, D.C.

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

Dimson, E., and P. Marsh. 1986. Event study methodologies and the size effect: The case of UK presses recommendations. *Journal of Financial Economics* 17:113–42.

Dittmar, A., and J. Mahrt-Smith. 2007. Corporate governance and the value of cash holdings. *Journal of Financial Economics* 83:599–634.

Doidge, C. 2004a. Do changes in laws matter for ownership and control? Evidence from emerging markets companies that list in the U.S. Working paper. University of Toronto.

Doidge, C. 2004b.U.S. cross-listings and the private benefits of control: Evidence from dual class companies. *Journal of Financial Economics* 72:519–54.

Doidge, C., G. A. Karolyi, and R. Stulz. 2004. Why are foreign companies that are listed in the U.S. worth more? *Journal of Financial Economics* 71:205–38.

Domowitz, I., J. Glen, and A. Madhavan. 1997. Market segmentation and stock prices: Evidence from an emerging market. *Journal of Finance* 52:1059–85.

Domowitz, I., J. Glen, and A. Madhavan. 1998. International cross-listing and order flow migration: Evidence from an emerging market. *Journal of Finance* 53(6):2001–27.

DuCharme, L., P. Malatesta, and S. Sefcik. 2004. Earnings management, stock issues, and shareholder lawsuits. *Journal of Financial Economics* 71(January):27–49.

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(Supplement):1–30.

Eckbo, B. Espen, V. Maksimovic, and J. Williams. 1990. Consistent estimation of cross-sectional models in event studies. *Review of Financial Studies* 3:343–65.

Edelman, R. B., and K. H. Baker. 1993. The impact of company pre-listing attributes on the market reaction to NYSE listings. *Financial Review* 28:431–48.

Efron, B. 1979. Bootstrap methods: Another look at the jackknife. *Annals of Statistics* 7:1–26.

Enders, Walter. 2004.*Applied econometric time series.*2nd ed.Wiley series in probability and mathematical statistics. Hoboken, NJ: Wiley.

Engle R F III. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50:987–1008.

Epstein, L. G., and S. M. Turnbull. 1980. Capital asset prices and the temporal resolution of uncertainty. *Journal of Finance* 35:627–643.

Errunza, V., and E. Losq. 1985. International asset pricing under mild segmentation: Theory and test. *Journal of Finance* 40:105–24.

Eun, C., and S. Janakiramanan. 1986. A model of international asset pricing with a constraint on the foreign equity ownership. *Journal of Finance* 41:1015–124.

Fabozzi, F., and J. C. Francis. 1977. Stability tests for alphas and betas over bull and bear market conditions. *Journal of Finance* 32:1093–99.

Fabozzi, F. J., and R. A. Hershkoff. 1979. The effect of the decision to list on a stock's systematic risk. *Research of Business and Economic Research* 14(Fall):77–82.

Fairfield, P., J. Whisenant, and T. Yohn. 2003. Accrued earnings and growth: implications for current profitability and market mispricing. *Accounting Review* 78:353–71.

Fairfield, P. M., S. Whisenant, and T. L. Yohn. 2003. The differential persistence of accruals and cash flows for future operating income versus future profitability. *Review of Accounting Studies* 8(2/3):221–43.

Fama, E. 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance* 25:383–417.

Fama, E. Jan. 1965b.The behavior of stock-market prices.*Journal of Business* 38(1):34–105.

Fama, E. 1971.Risk, return, and equilibrium.*Journal of Political Economy* 79(1):30–55.

Fama, E. 1974.The empirical relationships between dividend and investment decisions of firms.*American Economic Review* June:304–314.

Fama, E. F. 1991. Efficient capital markets: II. *Journal of Finance* 46:1575–1617.

Fama, E., and K. French. 1993. Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics* 33:3–56.

Fama, E., and J. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81:607–36.

Fama, E. F. 1976. Reply.*Journal of Finance* 31(1):143–45.

Fama, E. F. 1976. *Foundations of finance*.New York: Basic Books.

Fama, E. F. 1996. Multifactor portfolio efficiency and multifactor asset pricing.*Journal of Financial and Quantitative Studies* 31(4):441–65.

Fama, E. F., and K. R. French. 1995. Size and book-to-market factors in earnings and returns. *Journal of Finance* 50:131–55.

Fama, E. F., and K. R. French. 1992. The cross-section of expected stock returns. *Journal of Finance* 47:427–65.

Fama, E. F., L. Fisher, M. C. Jensen, and R. Roll. 1969. The adjustment of stock prices to new information. *International Economic Review* 10:1–21.

Fanto, J. A., and R. S. Karmel. 1997. A report on the attitudes of foreign companies regarding a U.S. listing. *Stanford Journal of Law, Business, and Finance* 3:51–83.

Fedyk, T., Z. Singer, and T. Sougiannis. 2010. Does the accrual anomaly end when abnormal accruals reverse? Working paper.Arizona State University, McGill University, and University of Illinois at Urbana-Champaign.

Ferreira, M. A., and P. P. Matos. 2008. The color of investors' money: The role of institutional investors around the world. *Journal of Financial Economics* 88:499–533.

Foerster, S. R., and G. A. Karolyi. 1993. International listings of stocks: The case of Canada and the U.S.*Journal of International Business Studies* 24(4):763–84.

Foerster, S. R., and G. A. Karolyi. 1998. Multimarket trading and liquidity: A transaction data analysis of Canada-U.S. inter-listings. *Journal of International Financial Markets, Institutions, and Money* 8(3–4):393–412.

Foerster, S. R., and G.A Karolyi. 1999. The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United States. *Journal of Finance* 54(3):981–1013.

Foucault, T., and A. J. Menkveld. 2008. Competition for order flow and smart order routing systems. *Journal of Finance* 63:119–58.

Freund, R. J., and R. C. Littell. 2000. *SAS system for regression.* 3rd ed. Cary, NC: SAS Institute.

Froot, K., and. J. Frankel, 1987. Using survey data to test standard propositions regarding exchange rate expectations.*American Economic Review* 77(1):133–53.

Froot, K. A. 1989. Consistent covariance matrix estimation with cross-sectional dependence and heteroscedasticity in financial data.*Journal of Financial and Quantitative Analysis* 24:333–55.

Froot, K., and R. Thaler. 1990. Anomalies: Foreign exchange. *Journal of Economic Perspectives* 4(3):179–92.

Frost, C., and W. Kinney. 1996. Disclosure choices of foreign registrants in the United States. *Journal of Accounting Research* 28:25–48.

Fuerst, O. 1998.A theoretical analysis of the investor protection regulations argument for global listing of stocks.Working paper.Yale University.

Furst, R. W. 1970. Does listing increase the market price of common stocks? *Journal of Business* 43:174–80.

Giaccotto, C., and J. M. Sfiridis. 1996. Hypothesis testing in event studies: The case of variance changes. *Journal of Economics and Business* 48:349–70.

Godfrey, L. G. 1978. Testing for multiplicative heteroscedasticity.*Journal of Econometrics* 8:227–36.

Goetzmann, W. N., and R. G. Ibbotson. 1994. Do winners repeat? *Journal of Portfolio Management* 20(2):9–18.

Goldberg, M. A. and A. Vora. 1981. The inconsistency of the relationship between security and market returns. *Journal of Economics and Business* 33:97–107.

Goulet, W. M. 1974. Price changes, managerial actions, and insider trading at the time of listing. *Financial Management* 3(Spring):30–36.

Gozzi, J. C., R. Levine, and S. L. Schmukler. 2008. Patterns of international capital raisings. Policy research working paper no. 4687.World Bank. Available at SSRN: http://ssrn.com/abstract=1233063.

Graham, B., and D. L. Dodd. 1934. *Security analysis.* New York: McGraw-Hill.

Grammatikos, T., and A. Saunders. 1986. Futures price variability: A test of maturity and volume effects. *Journal of Business* 59:319–30.

Greene, W. 2003.A interpreting estimated parameters and measuring individual heterogeneity in random coefficient models.Working paper 03–19.New York University.

Greene, W. H. 2003. *Econometric analysis.* 5th ed.Upper Saddle River, NJ: Prentice Hall.

Gregory, A. 1997.An examination of the long-run performance of UK acquiring firms.*Journal of Business Finance Accounting* 24:971–1002.

Griffin, J. M., X. Ji, and J. S. Martin. 2003. Momentum investing and business cycle risk: Evidence from pole to pole. *Journal of Finance* 58:2515–47.

Guidolin, M., and A. Timmermann.2005a. Strategic asset allocation and consumption decisions under multivariate regime switching.Working paper no. 2005-002A.Federal Reserve Bank of St. Louis.

Guidolin, M., and A. Timmermann.2005b. Size and value anomalies under regime switching.Working paper no. 2005-007A.Federal Reserve Bank of St. Louis.

Hahn, J., and H. Lee. 2006. Yield Spreads as Alternative Risk Factors for Size and Book-to-Market.*Journal of Financial and Quantitative Analysis* 41:245–269.

Hall, P. 1992. On the removal of skewness by transformation.*Journal of the Royal Statistical Society*, Series B (Methodological), 54(1):221–28.

Hargis, K. W., and J. P. Mei. 2000. What are the sources of country and industry diversification? Working paper no.FIN-00-045.New York University. Available at SSRN: http://ssrn.com/abstract=1300267.

Harris, M. S., and K. A. Muller III. 1999. The market valuation of IAS versus U.S. GAAP accounting measures using form 20-F reconciliation. *Journal of Accounting and Economics* 26:286–312.

Haugen, R. A., and N. L. Baker. 1996. Commonality in the determinants of expected stock returns. *Journal of Financial Economics* 41:401–39.

Haw, I., V. S. Pastena, and S. B. Lilien. 1990. Market manifestation of nonpublic information prior to mergers: The effect of capital structure. *Accounting Review* 65(April):432–51.

Healy, P. M. 1985. The effect of bonus schemes on accounting decisions.*Journal of Accounting and Economics* 7:85–107.

Healy, P. M., and J. M. Wahlen. 1999. A review of the earnings management literature and its implications for standard setting. *Accounting Horizons* 13(4):365–83.

Hirshleifer, D., K. Hou, S. Teoh, and Y. Zhang. 2004. Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics* 38:297–331.

Horowitz, Joel L., 2001. The Bootstrap.In: J.J. Heckman and E.E. Leamer (eds.), *Handbook of Econometrics*, Ed. 1, Vol. 5, Ch. 52, pp. 3159-3228.Elsevier.

Hsieh, D. A. 1989. Modeling heteroscedasticity in daily foreign-exchange rates.*Journal of Business and Economic Statistics* 7:307–17.

Hwang, C. Y., and N. Jayaraman. 1993. The post-listing puzzle: Evidence from Tokyo stock exchange listings. *Pacific-Basin Finance Journal* 1:111–26.

Ibbotson, R. G. 1975. Price performance of common stock new issues.*Journal of Financial Economics* 2:232–72.

Ibbotson, R. G., and J. F. Jaffe. 1975. "Hot issue" markets. *Journal of Finance* 30:1027–42.

Ibbotson R., J. Ritter, and J. L. Sindelar. 1994. The markets' problems with the pricing of initial public offerings. *Journal of Applied Corporate Finance* Summer:66–74.

Ikenberry, D., G. Rankine, and E. Stice. 1996. What do stock splits really signal? *Journal of Financial and Quantitative Analysis* 31:357–76.

Iqbal, Z., and P. L. Dheeriya. 1991. A comparison of the market model and random coefficient model using mergers as an event. *Journal of Economics and Business* 43:87–93.

Jegadeesh, N. 1990.Evidence of predictable behavior of security returns.*Journal of Finance* 45:881−98.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implication for stock market efficiency. *Journal of Finance* 48:65−91.

Jegadeesh, N., and S. Titman. 1995. Over-reaction, delayed reaction, and contrarian profits. *Review of Financial Studies* 8:973−93.

Jegadeesh, N., and S. Titman. 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance* 56:699−720.

Jegadeesh, N., and S. Titman. 2002. Momentum. Working paper.University of Illinois. Available at SSRN: http://ssrn.com/abstract=299107 or doi:10.2139/ssrn.299107.

Jegadeesh, N., M. Weinstein, and I. Welch. 1993. An empirical investigation of IPO returns and subsequent equity offerings. *Journal of Financial Economics* 34:153–75.

Jensen, M. 1986. Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review* 76:323–29.

Jo, H., and Y. Kim. 2007. Disclosure frequency and earnings management. *Journal of Financial Economics* 84:561–90.

Jones, C., and O. Lamont. 2002. Short-sale constraints and stock returns. *Journal of Financial Economics* 66:207–39.

Jones, J. 1991. Earnings management during import relief investigations.*Journal of Accounting Research* 29(2):193–228.

Kahneman, D., and A. Tversky. 1979. Prospect theory: an analysis of decision under risk. *Econometrica* 47:263–91.

Kahneman, D., and A. Tversky. 1982. The simulation heuristic. In *Judgment under uncertainty: Heuristics and biases*, D. Kahneman, P. Slovic, and A. Tversky, eds., pp. 201–08. New York: CambridgeUniversity Press.

Kalay, A., and U. Lowenstein. 1985. Predictable events and excess returns: The case of dividend announcements. *Journal of Financial Economics* 14:423–50.

Kang, S., and K. Sivaramakrishnan. 1995. Issues in testing earnings management and an instrumental variable approach. *Journal of Accounting Research* 33(2):353–67.

Kaplan, R., and R. Roll. 1972. Investor evaluation of accounting information: Some empirical evidence. *Journal of Business*, 45, 2, *225-257*.

Karolyi, G. A. 2003. Does international financial contagion really exist? *Journal of International Finance*6(2):179–199.

Karolyi, G. A. 2006. The world of cross-listings and cross-listings of the world: Challenging conventional wisdom. *Review of Finance* 10(1):99–152.

Karolyi, G. A., and R. M. Stulz. 2002. Are financial assets priced locally or globally? Working paper series, vol. w8994.NBER. Available at SSRN: http://ssrn.com/abstract=315991.

King, M. R., and D. Segal. 2006. The long-term effects of cross-listing, investor recognition, and ownership structure on valuation. (October 1). EFA 2007 Ljubljana meetings paper. Available at SSRN: http://ssrn.com/abstract=924585.

Klein, A., and J. Rosenfeld. 1987. The influence of market conditions on event-study residuals. *Journal of Financial and Quantitative Analysis* 22:345–51.

Ko, K., I. Lee, and K. Yun. 1997. Foreign listings, firm value, and volatility: The case of Japanese firms listing on the U.S. stock markets. *Japan and the World Economy* 9:57–69.

Kothari, S., A. Leone, and C. Wasley. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39:163–97.

Kothari, S., J. Shanken, and R. Sloan. 1995. Another look at the cross-section ofexpected stock returns.*Journal of Finance* 50:185–224.

Lakonishok, J., A. Shleifer, and R. Vishny. 1994. Contrarian investment, extrapolation, and risk. *Journal of Finance* 49:1541–78.

Lakonishok, J., and T. Vermaelen. 1990. Anomalous price behavior around repurchase tender offers. *Journal of Finance* 45:455–77.

Lang, M. H., K. V. Lins, and D. P. Miller. 2003. ADRs, analysts, and accuracy: Does cross-listing in the United States improve a firm's information environment and increase market value? *Journal of Accounting Research* 41:317–45.

Lang, M., J. S. Raedy, and M. H. Yetman. 2003. How representative are firms that are cross-listed in the United States? An analysis of accounting quality.*Journal of Accounting Research* 41(2):363–386.

Lang, M., J. S. Raedy, and M. Yetman. 2003. How representative are cross-listed firms? An analysis of firm performance and accounting quality.*Journal of Accounting Research*41:363–86.

Lang, M., J. S. Raedy, and W. Wilson. 2006. Earnings management and cross-listing: Are reconciled earnings comparable to U.S. earnings? *Journal of Accounting and Economics* 42:255–83.

La Porta, R., F. Lopez-De-Silanes, and A. Shleifer. 1998. Legal determinants of external finance. *Journal of Finance* 52(3):1131–50.

La Porta, R. F. Lopez-de-Silanes, A. Shleifer, and R. W. Vishny. 1998. Law and finance. *Journal of Political Economy* 106:1113–55.

La Porta, R., F. Lopez-De-Silanes, A. Shleifer, and R. Vishny. 2000. Investor protection and corporate governance. *Journal of Financial Economics* 58 (1–2):3–27.

Lau, S. T., J. D. Diltz, and V. P. Apilado. 1994. Valuation effects of international stock exchange listings. *Journal of Banking and Finance* 18(4):743–55.

Lee, C., A. Shleifer, and T. Thaler. 1991. Investor sentiment and the closed-end fund puzzle. *Journal of Finance* 46:75–109.

Lee, D. 2003. Why does shareholder wealth increase when foreign firms announce their listings in the U.S.? Working paper.Ohio State University.

Lee, D. S. 1992. Management buyout proposals and inside information.*Journal of Finance* 47(3):1061–79.

Lee, I. 1991. The impact of overseas listing on shareholder wealth: The case of the London and Toronto stock exchanges. *Journal of Business Finance and Accounting* 18:582–92.

Lehmann, B. 1990.Fads, martingales, and market efficiency.*Quarterly Journal of Economics* 105:1–28.

Leroy, S. 1973. Risk aversion and the martingale property of stock returns.*International Economic Review* 14:436–46.

Leuz, C. 2003. Proprietary versus non-proprietary disclosures: Evidence from Germany. Available at SSRN: http://ssrn.com/abstract=99861.

Leuz, C., K. Lins, and F. Warnock. 2005. Adverse selection and home bias: Do foreigners invest less in poorly governed firms? Working paper.University of Utah.

Licht, A. N. 2003. Cross-listing and corporate governance: Bonding or avoiding? *Chicago Journal of International Law* 4. Available at SSRN: http://ssrn.com/abstract=382660 or doi:10.2139/ssrn.382660.

Liew, J., and M. Vassalou. 2000. Can book-to-market, size, and momentum be risk factors that predict economic growth? *Journal of Financial Economics* 57:221–45.

Linn, S. C., and J. J. McConnell. 1983. An empirical investigation of the impact of "antitakeover" amendments on common stock prices. *Journal of Financial Economics* 11(1–4):361–99.

Lintner, J. 1965. The valuation of risk assets and selection of risky investments in stock portfolios and capital budgets.*Review of Economics and Statistics* 47:13–37.

Liu, R. Y. 1988. Bootstrap procedures under some non-IID models. *Annals of Statistics* 16:1696–1708.

Liu, R.Y. and K. Singh (1992) Moving blocks jackknife and bootstrap capture weak dependence. In R. LePage and L. Billiard (eds.), *Exploring the limits of the bootstrap*, pp. 224–48. New York: Wiley.

Lo, A. W., and A. C. MacKinlay. 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. *Review of Financial Studies* 1:41–66.

Lo, A. W., and A. C. MacKinlay. 1996. The econometrics of financial markets. Princeton University Press.

Lucas, R. 1978. Asset prices in an exchange economy. *Econometrica* 46:1429–46.

Lyon, J. D., B. M. Barber, and C-L.Tsai. 1999. Improved methods for tests of long-run abnormal stock returns. *Journal of Finance* 54(1):165–201.

MacKinlay, A. C. 1995. Multifactor models do not explain deviation from the capital asset pricing models. *Journal of Financial Economics* 38:3–28.

Mais, E. L., W. T. Moore, and R. C. Rogers. 1989. A re-examination of shareholder wealth effects of calls of convertible preferred stock. *Journal of Finance* 44:1401–10.

Mandelker, G. 1974. Risk and return: The case of merging firms. *Journal of Financial Economics* 1:303–35.

Mann, S., and N. Sicherman. 1991. The agency costs of free cash flow: Acquisition activity and equity issues. *Journal of Business* 64:213–27.

Marais, M. Laurentius. 1984. An application of the bootstrap method to the analysis of squared standardized market model prediction errors. *Journal of Accounting Research* 22(Supplement):34–54.

Markovitch D. G., J. H. Steckel, and B. Yeung. 2005. Using capital markets as market intelligence: Evidence from the pharmaceutical industry. *Management Science* 51(10):1467–80.

Markowitz, H. 1952. Portfolio selection.*Journal of Finance* 7(1):77-91.

McConnell, J. J., and G. Sanger. 1987. The puzzle in post-listing common stock returns. *Journal of Finance* 42:119–40.

McLeod, A. I., and W. K. Li. 1983. Diagnostic checking ARMA (Autoregressive moving average model) time-series models using squared-residual autocorrelations. *Journal of Time-Series Analysis* 4:269–73.

McNichols, M. F. 2000. Research design issues in earnings management studies. *Journal of Accounting and Public Policy* 19(4–5):313-345.

McNichols, M. F. 2002. Discussion: The quality of accruals and earnings: The role of accruals estimation errors. *Accounting Review* 77(Supplement):61–69.

Merjos, A., 1962. Going on the big board: Stocks act better before listing than right afterward.Barron's.January 29, 5 and 14.

Merjos, A. 1963. Like money in the bank: big board listing, the record suggests is a valuable asset. *Barron's*.July 8, 9, and 13.

Merjos, A. 1967.Up on the curb.*Barron's*.May 1, 9, 10, and 15.

Merton, R. C. 1973. An inter-temporal CAPM.*Econometrica* 41(5):867–87.

Merton, R. C. 1987. Presidential address: A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42:483–510.

Mikkelson, W., and M. Partch. 1988. Withdrawn security offerings. *Journal of Financial and Quantitative Analysis* 23:119–33.

Miller, D. P. 1999. The market reaction to international cross-listings: Evidence from depositary receipts. *Journal of Financial Economics* 51(1):103–23.

Mittoo, U. 1992a. Additional evidence on integration in the Canadian stock market.*Journal of Finance* 62(5), 2035–54.

Mittoo, U. 1992b. Managerial perceptions of the net benefits of foreign listing: Canadian evidence. *Journal of International Financial Management and Accounting* 4:40–62.

Moel, A. 1999. The role of information disclosure on stock market listing decisions: The case of foreign companies listing in the U.S. Working paper. Harvard Business School.

Myers, R. H. 1990. *Classical and modern regression with applications*, 2nd ed. *The Duxbury advanced series in statistics and decision sciences.* Boston, MA: PWS-Kent.

Ndubizu, A. 2007.Gordian.*Accounting Review* 82(4):1009–30.

Pagano, M., A. A. Roell, and J. Zechner. 2002. The geography of equity listing: Why do European companies list abroad? *Journal of Finance* 57:2651–94.

Patell, J. 1976. Corporate forecasts of earnings per share and stock price behavior: Empirical tests. *Journal of Accounting Research* 14:246–76.

Patell, J., and M. Wolfson. 1979. Anticipated information releases reflected in call option prices. *Journal of Accounting and Economics* 1:117–40.

Petkova, R. 2006. Do the Fama-French Factors Proxy for Innovations in Predictive Variables? *Journal of Finance* 61:581–612.

Pincus, M., S. Rajgopal, and M. Venkatachalam. 2007. The accrual anomaly: International evidence. *Accounting Review* 82:169–203.

Prabhala, N. R. 1997. Conditional methods in event studies and an equilibrium justification for standard event-study procedures.*Review of Financial Studies* 10:1–38.

Reese, W. A. J., and M. S. Weisbach. 2002. Protection of minority shareholder interests, cross-listings in the United States, and subsequent equity offerings. *Journal of Financial Economics* 66:65–104.

Reints, W. W., and P. A. Vandenberg. 1975. The impact of changes in trading location on a security's systematic risk. *Journal of Financial and Quantitative Analysis 10*:881–890.

Richardson, M., and T. Smith. 1989. Tests of financial models in the presence of overlapping observations. *Review of Financial Studies* 4:227–54.

Richardson, M. P., and J. H. Stock. 1990. Drawing inferences from statistics based on multi-year asset returns. Working paper series, vol. w3335.NBER. Available at SSRN: http://ssrn.com/abstract=468840.

Robichek, A. A., and S. C. Myers. 1966. Valuation of the firm: Effects of uncertainty in a market context. *Journal of Finance* 21:215–27.

Roll, R. 1978. Ambiguity when performance is measured by the securities market line. *Journal of Finance* 33(4):1051.

Rosenberg, B., K. Reid, and R. Lanstein. 1985. Persuasive evidence of the market inefficiency. *Journal of Portfolio Management* 11:9–17.

Rosenstein, J., and S. Wyatt. 1990. Outside directors, board independence, and shareholder wealth. *Journal of Financial Economics* 26:175–92.

Ross, S. 1976. The arbitrage theory of capital asset pricing.*Journal of Economic Theory* 13:341–60.

Rothman, M. 1995. The international dual-listing of stocks and tests of capital market segmentation.Working paper.University of Chicago.

Rouwenhorst, K. 1999. Local return factors and turnover in emerging stock markets.*Journal of Finance* 54:1439–64.

Rouwenhorst, K. G. 1998. International momentum strategies.*Journal of Finance* 53:267–84.

Sagi, J., and M. Seasholes. 2007. Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics* 84:389–434.

Sanders, R. W. Jr., and R. P. Robins. 1991. Discriminating between wealth and information effects in event studies in accounting and finance research. *Review of Quantitative Finance and Accounting* 1(3):307–30.

Sanger, G. C., and J. J. McConnell. 1986. Stock exchange listings, company value, and security market efficiency: The impact of NASDAQ. *Journal of Financial and Quantitative Analysis* 21(1):1–25.

Sanger, G. C., and J. D. Peterson. 1990. An empirical analysis of common stock delistings. *Journal of Financial and Quantitative Analysis* 25(2):261–72.

Scheinkman, J. A., and W. Xiong. 2003. Overconfidence and speculative bubbles. 13th annual Utah Winter Finance Conference; AFA 2003 Washington, D.C. meetings.

Schill, M. J., M. J. Cooper, and G. Gulen. 2008. Asset growth and the cross-section of stock returns. *Journal of Finance*63(4):1609–51.

Schipper, K., and A. Smith. 1986. A comparison of equity carve-outs and seasoned equity offerings. *Journal of Financial Economics* 15:153–86.

Schipper, K., and R. Thompson. 1986. The impact of merger-related relationships on the shareholders of acquiring companies. *Journal of Accounting Research* 21:184–221.

Scholes, M., and J. T. Williams.1977.Estimating betas from no synchronous data.*Journal of Financial Economics* 5(3):309–27.

Sefcik, S., and R. Thompson. 1986. An approach to statistical inference in cross-sectional models with security abnormal returns as dependent variables. *Journal of Accounting Research* 24:316–34.

Sharpe, W. F. 1964. Capital asset prices: A theory of equilibrium under conditions of risk. *Journal of Finance* 19:425–42.

Shivakumar, L. 2000. Do firms mislead investors by overstating earnings before seasoned equity offerings? *Journal of Accounting and Economics* 29:339–372.

Siganos, A., and P. Chelley-Steeley. 2006. Momentum profits following bull and bear markets. *Journal of Asset Management* 6:381–88.

Smith, A. 1937.*The wealth of nations.*Modern Library Edition.New York: Random House.

Smith, Katherine, and Sofianos, 1997, The impact of an NYSE listing on global trading of non-U.S stocks, NYSE working paper 97-02.

Stapleton R., and M. Subrahmanyam. 1977. Market imperfections, capital market equilibrium and corporate finance. *Journal of Finance* 32:307–19.

Stulz, R. M. 1999. Globalization, corporate finance, and the cost of capital.*Journal of Applied Corporate Finance* 12:8–25.

Teoh, S. H., I. Welch, and T. J. Wong. 1998. Earnings management and the long-term market performance of initial public offerings. *Journal of Finance* 53:1935–74.

Thompson, J. E. 1988. More methods that make little difference in event studies.*Journal of Business Finance and Accounting* 15:77–86.

Thompson R. 1978. The information content of discounts and premiums on closed-end fund shares.*Journal of Financial Economics* 6:151–86.

Titman, S., J. Wei, and F. Xie. 2004. Capital investments and stock returns. *Journal of Financial and Quantitative Analysis* 39:677–700.

Tobin, J. 1958. Liquidity preference as behavior towards risk.*Review of Economic Studies* 25(1):65–86.

Torabzadeh, K., W. Bertin, and T. Zivney. 1992. Valuation effects of international listings. *Global Finance Journal* 3:159–170.

Tversky, A., and D. Kahneman. 1981. The framing of decisions and the psychology of choice. *Science* 211(4481):453–58.

Tversky, A., and D. Kahneman. 1992. Advances in prospect theory: cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5:297–323.

Valero, M., H. W. Lee, and N. Cai. 2009. Cross-listing pursuit of unseasoned foreign firms after going public in the U.S.*Journal of Business Research* 62(8):797–804.

Van Home, J. C. 1970. New listings and their price behavior.*Journal of Finance*25:783–794.

Varela O., and S. Lee. 1993a. International listings, the security market line, and capital market integration: The case of U.S. listings on the London stock exchange. *Journal of Business Finance and Accounting* 20:843–63.

Varela O., and S. Lee. 1993b. The combined effects of international listing on the security market line and systematic risk for listings on the London and Tokyo stock exchanges.In *International financial market integration*, S. Stansell, ed. Cambridge, MA: Blackwell Publishers, 367–88.

Vassalou, M. 2003. News related to future GDP growth as a risk factor in equity returns. *Journal of Financial Economics* 68:47–73.

Verbeek, M. 2004. *A Guide to Modern Econometrics*. 2nd ed. Chichester: Wiley.

Watts, R.L.1978. Systematic "abnormal" returns after quarterly earnings announcements.*Journal of Financial Economics*, 6, 127–150.

White. H. 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity.*Econometrica* 48:817–38.

Wilmott Forums - Stochastic Processes accomodating Higher Moments, http://www.wilmott.com/messageview.cfm?catid=8&threadid=4178 (accessed August 4, 2011).

Wooldridge, J. 2003. *Introductory econometrics: A modern approach*. 2nd ed. Mason, OH: Thomson/South-Western.

Wooldridge, J. M. 2002. *Econometric analysis of cross section and panel data.*Cambridge, MA: MIT Press.

Ying, L. K. W., W. G. Lewellen, G. G. Schlabram, and R. C. Lease. 1977. Stock exchange listings and securities returns. *Journal of Financial and Quantitative Analysis* September 12(September):415–32.

Zweig, M. E. 1973. An investor expectations stock price predictive model using closed-end fund premiums.*Journal of Finance* 28:67–87.

Table 1: Basic Statistical Measures for Variable R_t

Table 1			
Location		Variability	
Mean	0.001496	Std. dev.	0.04323
Median	0.000000	Variance	0.00187
Mode	0.000000	Range	1.79408
		Interquartile range	0.02951

Table 2: Statistical Tests for the Mean of the Variable R_T, and Provides Evidence It Is Significantly Different from Zero

Table 2: Tests for Location: Mu0 = 0				
Test	Statistic		*p*-value	
Student's *t*	*T*	6.944	Pr > |*t*|	<.0001
Sign	*M*	121	Pr >= |*M*|	0.2198
Signed rank	*S*	4,943,407	Pr >= |*S*|	0.0238

Table 3: Goodness-of-fit Daily Returns against Normal Distribution

Table 3: Goodness-of-fit Tests for Normal Distribution				
Test	Statistic		p-value	
Kolmogorov–Smirnov	D	0.13245	Pr >D	<0.010
Cramer–von Mises	$W\text{-}Sq$	320.49934	Pr >$W\text{-}Sq$	<0.005
Anderson–Darling	$A\text{-}Sq$	1,737.28791	Pr >$A\text{-}Sq$	<0.005

Table 4: Domestic Mean Daily Returns by Companies and by Country along with the Host Mean Daily Market Index Return (Dow Jones Industrial Average)

Country	Company	Daily domestic returns			Host market index returns		
		Mean	*Std. dev.*	*# Obs*	*Mean*	*Std. dev.*	*# Obs*
London	BHP Billiton PLC (BBL)	.00134	.01933	1,304	.00006	.01107	1,304
	Royal Dutch Shell PLC (RDS)	.00054	.01275	1,303	.00039	.00787	1,303
	Total	.00094	.01637	2,607	.00022	.00960	2,607
Canada	Compton Petroleum Corp. (CMZ)	.00106	.02246	1,304	.00039	.00786	1,304
	Precision Drilling Trust (PDS)	.00056	.01809	1,304	.00039	.00786	1,304
	Gerdau Ameristeel Corp. (GNA)	.00220	.03379	1,564	.00023	.00966	1,564
	Silver Wheaton Corp. (SLW)	.00431	.06456	1,303	.00039	.00787	1,303
	Penn West Energy Trust (PWE)	.00018	.02344	1,304	–.0001	.01229	1,304
	Baytex Energy Trust (BTE)	.00061	.02624	1,304	–.0001	.01229	1,304
	Labopharm Inc. (DDSS)	.00022	.04985	1,304	–.0001	.01229	1,304
	Teck Resources Lt. (TCK)	.00026	.03665	1,304	–.0001	.01229	1,304
	SXC Health Solutions Corp. (SXCI)	.00235	.03035	1,303	.00007	.01369	1,303
	Domtar Corp (UFS)	.00005	.03993	1,303	.00007	.01369	1,303
	Transition Therapeutics Inc. (TTHI)	.00041	.04618	1,304	.00007	.01368	1,304
	Thompson Creek Metals Company Inc. (TC)	.00432	.06331	1,304	.00007	.01368	1,304
	Westport Innovations Inc. (WPRT)	.00247	.04909	1,044	.00008	.01496	1,044
	Total	.00146	.04117	16,949	.00012	.01186	16,949
India	Tata Motors Ltd. (TTM)	.00170	.02396	1,564	.00023	.00966	1,564
	Patni Computer Systems Ltd. (PTI)	.00081	.02569	1,004	.00025	.00716	1,004
	Sterlite Industries Ltd. (SLT)	.00213	.03823	1,304	.00007	.01368	1,304
	Total	.00161	.02992	3,872	.00018	.01067	3,872
Australia	Genetic Technologies Ltd. (GENE)	.00087	.04620	1,303	.00039	.00787	1,303
	Sims Metal Management Ltd. (SMS)	.00099	.03353	1,044	.00008	.01496	1,044
	Total	.00093	.04104	2,347	.00025	.01157	2,347

Table 4: Domestic Mean Daily Returns by Companies and by Country along with the Host Mean Daily Market Index Return (Dow Jones Industrial Average) (cont.)

Country	Company	Daily domestic returns			Host market index returns		
		Mean	*Std. dev.*	*# Obs*	*Mean*	*Std. dev.*	*# Obs*
Israel	**Pointer Telocation Ltd. (PNTR)**	.00035	.06040	1,304	–.0001	.01229	1,304
	Ituran Location & Control Ltd. (ITRN)	.00157	.02055	1,303	.00039	.00787	1,303
	Starlims Technologies Ltd. (LIMS)	.00046	.02689	1,043	–.0001	.01333	1,043
	Total	.00082	.04074	3,650	.00009	.01126	3,650
China	**Origin Agritech Ltd. (SEED)**	.00089	.03493	981	.00028	.00711	981
	American Oriental Bioengineer (AOB)	.00441	.06673	1,302	.00037	.00785	1,302
	Yucheng Technologies Ltd. (YTEC)	.00094	.03316	1,303	.00007	.01369	1,303
	China Security & Surveillance Inc. (CSR)	.00309	.08017	1,181	.00010	.01421	1,181
	General Steel Holdings Inc. (GSI)	.00325	.07681	1,304	.00007	.01368	1,304
	ReneSola Ltd. (SOL)	.00254	.06354	889	.00004	.01594	889
	Total	.00259	.06262	6,960	.00016	.01247	6,960
Germany	**Aixtron Aktiengesellschaft (AIXG)**	.00137	.03263	1,303	.00039	.00787	1,303
	Total	.00137	.03263	1,303	.00039	.00787	1,303
Brazil	**Gafisa S.A., (GFA)**	.00150	.04732	1,023	.00007	.01508	1,023
	Total	.00150	.04732	1,023	.00007	.01508	1,023
Argentina	**Petrobras Energia Participa (PZE)**	.00024	.02981	1,564	.00015	.01041	1,564
	Total	.00024	.02981	1,564	.00015	.01041	1,564

Table 5: Results of Testing H_0 (Parametric)

Table 5: Post-listing Anomaly Exists (Significant Negative CAAR(cumulative average abnormal return) in the Post-listing Period)

Market model: –DJIA(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision -weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	Portfolio time-series (CDA) *t*	CSectErr *t*	Skewness corrected *T1*
(–10, –6)	10	–1.54%	–1.83%	3:7	–0.760	–1.035	–0.391	–0.612	–0.603
(–5, –2)	10	1.44%	0.39%	5:5	0.178	0.198	0.409	0.628	0.681
(–1, +1)	10	8.91%	3.13%	6:4	1.682*	0.663	2.915**	1.121	1.568$
(–3, +3)	10	5.91%	1.37%	5:5	0.479	0.267	1.266	0.736	0.914
(+11, +50)	10	–21.39%	–18.41%	2:8(	–2.598**	–1.920*	–1.916*	–1.645*	–1.874*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (, <or), > correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for all parametric tests.**

Table 6: The Results of Testing H_A (Parametric)

Table 6: Post-listing Anomaly Does Not Exist (Weak Significant Positive CAAR in the Post-listing Period)									
Market model: +DJIA(0,+50)									
Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	Portfolio time-series (CDA) *t*	CSectErr *t*	Skewness corrected *T1*
(−10, −6)	22	−1.11%	−0.53%	11:11	−0.435	−0.411	−0.626	−0.771	−0.798
(−5, −2)	22	−1.46%	−1.04%	10:12	−0.981	−0.850	−0.919	−1.116	−1.151
(−1, +1)	22	0.54%	0.80%	14:8>	0.872	0.648	0.392	0.302	0.294
(−3, +3)	22	−0.18%	1.14%	12:10	0.816	0.583	−0.086	−0.075	−0.075
(+11, +50)	22	4.70%	6.58%	13:9	1.876*	1.761*	0.934	1.277	1.266

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for all parametric tests.**

Table 7: The Results of Testing H_{1A}, H_{1B}, H_{1C} (Parametric)

Table 7: Shows Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Negative and Explains the Anomaly. Hence, Companies Do Not Time the Market

Market model: –DJIA(0,+50)									
Days	***N***	**Mean cumulative abnormal return**	**Precision-weighted CAAR**	**Positive: Negative**	**Patell *Z***	**StdCsect *Z***	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Skewness corrected *T1***
(–10, –6)	6	–3.60%	–2.03%	1:5(	–0.544	–0.880	–0.693	–1.128	–1.155
(–5, –2)	6	–0.43%	0.39%	2:4	0.116	0.122	–0.092	–0.152	–0.153
(–1, +1)	6	0.10%	–1.60%	3:3	–0.557	–0.486	0.025	0.031	0.032
(–3, +3)	6	–3.46%	–2.52%	2:4	–0.572	–0.578	–0.563	–0.800	–0.729
(+11, +50)	6	–37.96%	–37.40%	0:6<	–3.410***	–2.437**	–2.587**	–2.425**	–4.656***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for all parametric tests.**

Table 8: The Results of Testing H_{2A}, H_{2B}, H_{2C} (Parametric)

Table 8: Shows Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market

Market model: +DJIA(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	Portfolio time-series (CDA) *t*	CSectErr *t*	Skewness corrected *T1*
(–10, –6)	3	1.67%	3.75%	2:1	0.828	0.913	0.277	0.449	0.367
(–5, –2)	3	–2.12%	1.99%	1:2	0.498	0.194	–0.395	–0.241	–0.240
(–1, +1)	3	10.69%	8.40%	3:0>	2.408**	12.566***	2.296*	2.775**	4.473***
(–3, +3)	3	9.80%	10.02%	2:1	1.874*	1.410$	1.377$	1.504$	0.888
(+11, +50)	3	–23.08%	–21.87%	0:3(	–1.661*	–3.462***	–1.357$	–3.777***	–10.156***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for all parametric tests.**

Table 9: The Results of Testing H_{3A}, H_{3B}, H_{3C} (Parametric)

Table 9: Shows Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market (Inconclusive)

Market model: +DJIA(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	Portfolio time-series (CDA) *t*	CSectErr *t*	Skewness corrected *T1*
(–10, –6)	19	–1.55%	–0.99%	9:10	–0.797	–0.742	–0.836	–0.983	–1.030
(–5, –2)	19	–1.36%	–1.37%	9:10	–1.254	–1.423$	–0.818	–1.394$	–1.472$
(–1, +1)	19	–1.06%	–0.03%	11:8	–0.018	–0.014	–0.739	–0.612	–0.649
(–3, +3)	19	–1.76%	0.18%	10:9	0.133	0.096	–0.800	–0.709	–0.746
(+11, +50)	19	9.08%	9.65%	13:6>	2.678**	2.761**	1.730*	2.902**	3.422***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for all parametric tests.**

Table 10: The Results of Testing H_{4A}, H_{4B}, H_{4C} (Parametric)

Table 10: Shows Cases Where Post-listing Anomaly Does Not Exist (Insignificant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market

Market model: –DJIA(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	Portfolio time-series (CDA) *t*	CSectErr *t*	Skewness corrected *T1*
(–10, –6)	4	1.53%	–1.63%	2:2	–0.535	–0.541	0.253	0.372	0.438
(–5, –2)	4	4.25%	0.39%	3:1)	0.139	0.145	0.786	1.086	1.424$
(–1, +1)	4	22.12%	7.90%	3:1)	3.342***	0.885	4.717***	1.182	1.751*
(–3, +3)	4	19.96%	5.29%	3:1)	1.458$	0.541	2.786**	1.104	1.589$
(+11, +50)	4	3.47%	0.64%	2:2	0.068	0.087	0.203	0.197	0.213

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for all parametric tests.**

Table 11: Results of Testing H_0 (Non-parametric)

Table 11: Post-listing Anomaly Exists (Significant Negative CAAR in the Post-listing Period)

Market model: –DJIA(0,+50)

Days	N	Mean cumulative abnormal return	Positive: Negative	Generalized sign Z	Rank test Z	Jackknife Z	Signed rank
(–10, –6)	10	–1.54%	3:7	–0.831	–0.571	–1.778*	-9.500
(–5, –2)	10	1.44%	5:5	0.447	–0.021	0.227	2.500
(–1, +1)	10	8.91%	6:4	1.085	0.763	0.717	10.500
(–3, +3)	10	5.91%	5:5	0.447	–0.178	0.135	–0.500
(+11, +50)	10	–21.39%	2:8(	–1.470$	–2.115*	–2.184*	–17.500*

The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.

Table 12: The Results of Testing H_A (Non-parametric)

Table 12: Post-listing Anomaly Does Not Exist (Weak Significant Positive CAAR in the Post-listing Period)								
				Market model: +DJIA(0,+50)				
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Generalized sign *Z*	Rank test *Z*	Jackknife *Z*	Signed rank
(–10, –6)	22	–1.11%	11:11	0.399	–0.893	–0.548	–16.500
(–5, –2)	22	–1.46%	10:12	–0.029	–1.139	–1.267	–32.500
(–1, +1)	22	0.54%	14:8>	1.683*	0.998	0.483	21.500
(–3, +3)	22	–0.18%	12:10	0.827	0.652	0.090	12.500
(+11, +50)	22	4.70%	13:9	1.255	1.797*	1.757*	40.500$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 13: The Results of Testing H_{1A}, H_{1B}, H_{1C} (Non-parametric)

Table 13: Shows Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Negative and Explains the Anomaly. Hence, Companies Do Not Time the Market

Market model: –DJIA(0,+50)								
Days	N	**Mean cumulative abnormal return**	**Positive: Negative**	**Generalized sign Z**	**Rank test Z**	**Jackknife Z**	**Signed rank**
(–10, –6)	6	–3.60%	1:5(	–1.328$	–0.821	–1.504$	–6.500
(–5, –2)	6	–0.43%	2:4	–0.505	–0.072	0.227	–2.500
(–1, +1)	6	0.10%	3:3	0.319	–0.475	–0.076	0.500
(–3, +3)	6	–3.46%	2:4	–0.505	–0.649	–0.378	–3.500
(+11, +50)	6	–37.96%	0:6<	–2.151*	–2.570**	–4.256***	–10.500*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 14: The Results of Testing H_{2A}, H_{2B}, H_{2C}(Non-parametric)

Table 14: Shows Cases Where Post-Listing Anomaly Exists (Significant Negative Post-Listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market							
Market model: +DJIA(0,+50)							
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Generalized sign *Z***	**Rank test *Z***	**Jackknife *Z***	**Signed rank**
(–10, –6)	3	1.67%	2:1	0.725	0.372	0.480	1.000
(–5, –2)	3	–2.12%	1:2	–0.434	0.055	–0.167	–1.000
(–1, +1)	3	10.69%	3:0>	1.883*	2.570**	2.864**	3.000
(–3, +3)	3	9.80%	2:1	0.725	1.594$	1.551$	2.000
(+11, +50)	3	–23.08%	0:3(	–1.593$	–1.170	–4.256***	–3.000

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 15: The Results of Testing H_{3A}, H_{3B}, H_{3C}(Non-parametric)

Table 15: Shows Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market (Inconclusive)							
Market model: +DJIA(0,+50)							
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Generalized sign *Z*	Rank test *Z*	Jackknife *Z*	Signed rank
(–10, –6)	19	–1.55%	9:10	0.141	–1.099	–0.732	–20.000
(–5, –2)	19	–1.36%	9:10	0.141	–1.235	–1.460$	–26.000
(–1, +1)	19	–1.06%	11:8	1.062	0.043	–0.398	–2.000
(–3, +3)	19	–1.76%	10:9	0.602	0.062	–0.499	–2.000
(+11, +50)	19	9.08%	13:6>	1.983*	2.377**	3.097***	61.000**
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.							

Table 16: The Results of Testing H_{4A}, H_{4B}, H_{4C} (Non-parametric)

Table 16: Shows Cases Where Post-listing Anomaly Does Not Exist (Insignificant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market

Market model: –DJIA(0,+50)

Days	*N*	**Mean cumulative abnormal return**	**Positive: Negative**	**Generalized sign *Z***	**Rank test *Z***	**Jackknife *Z***	**Signed rank**
(–10, –6)	4	1.53%	2:2	0.316	0.114	–0.835	0.000
(–5, –2)	4	4.25%	3:1)	1.328$	0.051	0.034	3.000
(–1, +1)	4	22.12%	3:1)	1.328$	1.742*	0.897	4.000
(–3, +3)	4	19.96%	3:1)	1.328$	0.508	0.450	3.000
(+11, +50)	4	3.47%	2:2	0.316	–0.144	0.383	0.000

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 17: Results of Testing H_0 (Fama-French Procedure)

Table 17: Post-listing Anomaly Exists (Significant Negative CAAR in The Post-listing Period)							
Fama-French time-series model: –DJIA(0,+50)							
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***	**Signed rank**
(–10, –6)	10	0.44%	4:6	0.105	0.215	–0.163	–2.500
(–5, –2)	10	1.71%	4:6	0.456	0.687	–0.163	1.500
(–1, +1)	10	7.99%	6:4	2.467**	1.003	1.116	5.500
(–3, +3)	10	5.71%	5:5	1.154	0.720	0.476	–1.500
(+11, +50)	10	–14.62%	2:8(	–1.236	–1.524$	–1.442$	–17.500*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for parametric tests.**

Table 18: The Results of Testing H_A (Fama-French Procedure)

Table 18: Post-listing Anomaly Does Not Exist (Weak Significant Positive CAAR in the Post-listing Period)							
Fama-French time-series model: +DJIA(0,+50)							
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*	Signed rank
(–10, –6)	22	–0.17%	11:11	–0.090	–0.117	0.429	8.500
(–5, –2)	22	–1.06%	9:13	–0.620	–1.082	–0.428	–42.500$
(–1, +1)	22	0.74%	15:7>	0.501	0.446	2.141*	21.500
(–3, +3)	22	–0.09%	13:9)	–0.040	–0.039	1.285$	15.500
(+11, +50)	22	2.51%	14:8>	0.465	0.667	1.713*	25.500

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for parametric tests.**

Table 19: The Results of Testing H_{1A}, H_{1B}, H_{1C}(Fama-French Procedure)

Table 19: Shows Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Negative and Explains the Anomaly. Hence, Companies Do Not Time the Market							
Fama-French time-series model, –DJIA(0,+50)							
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***	**Signed rank**
(–10, –6)	6	–0.54%	3:3	–0.097	–0.222	0.373	–1.500
(–5, –2)	6	–0.16%	2:4	–0.032	–0.050	–0.453	–2.500
(–1, +1)	6	0.07%	3:3	0.017	0.020	0.373	–0.500
(–3, +3)	6	–2.86%	2:4	–0.437	–0.676	–0.453	–4.500
(+11, +50)	6	–31.63%	0:6<	–2.024*	–4.167***	–2.105*	–10.500*
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for parametric tests.							

Table 20: The Results of Testing H_{2A}, H_{2B}, H_{2C}(Fama-French Procedure)

Table 20: Shows Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market

Fama-French time-series model: +DJIA(0,+50)

Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*	Signed rank
(–10, –6)	3	2.62%	2:1	0.410	0.892	0.792	2.000
(–5, –2)	3	0.63%	1:2	0.110	0.109	–0.371	0.000
(–1, +1)	3	10.43%	3:0>	2.105*	2.829**	1.956*	3.000
(–3, +3)	3	10.66%	3:0>	1.409$	2.315*	1.956*	3.000
(+11, +50)	3	–23.97%	0:3(	–1.326$	–4.679***	–1.534$	-3.000

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for parametric tests.**

Table 21: The Results of Testing H_{3A}, H_{3B}, H_{3C} (Fama-French Procedure)

Table 21: Shows Cases Where Post-Listing Anomaly Does Not Exist (Significant Positive Post-Listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market(Inconclusive)

Fama-French time-series model: +DJIA(0,+50)

Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*	Signed rank
(–10, –6)	19	–0.61%	9:10	–0.316	–0.375	0.147	–2.000
(–5, –2)	19	–1.33%	8:11	–0.765	–1.610$	–0.313	–37.000$
(–1, +1)	19	–0.79%	12:7)	–0.526	–0.495	1.529$	–2.000
(–3, +3)	19	–1.79%	10:9	–0.780	–0.763	0.608	–3.000
(+11, +50)	19	6.69%	14:5>>	1.221	1.970*	2.450**	50.000*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for parametric tests.**

Table 22: The Results of Testing H_{4A}, H_{4B}, H_{4C} (Fama-French Procedure)

Table 22: Shows Cases Where Post-Listing Anomaly Does Not Exist (Insignificant Positive Post-Listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market							
Fama-French time-series model: –DJIA(0,+50)							
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*	Signed rank
(–10, –6)	4	1.90%	1:3	0.292	0.484	–0.714	–1.000
(–5, –2)	4	4.50%	2:2	0.773	1.110	0.296	2.000
(–1, +1)	4	19.87%	3:1)	3.938***	1.041	1.307$	2.000
(–3, +3)	4	18.55%	3:1)	2.408**	1.014	1.307$	2.000
(+11, +50)	4	10.90%	2:2	0.592	0.804	0.296	0.000
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test. The bootstrapping method is used for parametric tests.							

Table 23: Positive Low Book-to-Market Ratio (Characteristics Index–OLS Estimation Procedure)

Table 23: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive, and Does Not Explain the Anomaly. Hence, Companies Time the Market

Market model: +LOBTM(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*	Skewness corrected *T1*
(–10, –6)	3	1.66%	4.15%	2:1	0.862	0.959	0.448	0.827	0.362
(–5, –2)	3	0.77%	5.77%	1:2	0.840	0.379	0.127	–0.339	0.138
(–1, +1)	3	10.48%	8.17%	3:0>	2.353**	12.889***	2.754**	1.993*	4.628***
(–3, +3)	3	10.94%	12.11%	3:0>	2.037*	1.911*	2.319*	1.993*	1.339$
(+11, +50)	3	–24.78%	–24.77%	0:3(	–1.877*	–3.350***	–5.552***	–1.505$	–21.221***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 24: Positive Low Book-to-Market Ratio (Characteristics Index–GARCH Estimation Procedure)

Table 24: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market. Different Estimation Procedures Produce Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: +LOBTM(0,+50)

Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*	Skewness corrected *T1*
(–10, –6)	3	1.88%	2:1	0.293	0.575	0.579	0.468
(–5, –2)	3	1.15%	1:2	0.200	0.192	–0.576	0.206
(–1, +1)	3	10.61%	3:0>	2.128*	2.602**	1.734*	4.614***
(–3, +3)	3	11.39%	3:0>	1.496$	2.159*	1.734*	1.546$
(+11, +50)	3	–21.41%	0:3<	–1.176	–3.197***	–1.731*	–3.429***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 25: Negative Low Book-to-Market Ratio (Characteristics Index–OLS Estimation Procedure)

Table 25: Shows Some Cases Where Post-listing Anomaly Exists (Insignificant Negative Post-listing Period CAAR). Host Market Condition Is a Negative, and Explains the Anomaly. Hence, Companies Do Not Time the Market									
Market model: –LOBTM(0,+50)									
Days	***N***	**Mean cumulative abnormal return**	**Precision -weighted CAAR**	**Positive: Negative**	**Patell *Z***	**StdCsect *Z***	**CSectErr *t***	**Generalized sign *Z***	**Skewness corrected *T1***
(–10, –6)	7	0.97%	0.74%	4:3	0.208	0.148	0.243	0.671	0.229
(–5, –2)	7	1.40%	–0.34%	3:4	–0.167	–0.223	0.534	–0.089	0.621
(–1, +1)	7	9.32%	3.39%	5:2)	1.890*	0.631	0.788	1.432$	0.992
(–3, +3)	7	7.80%	2.60%	5:2)	0.853	0.375	0.651	1.432$	0.755
(+11, +50)	7	–1.03%	2.71%	4:3	0.500	0.524	–0.161	0.671	–0.161

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 26: Negative Low Book-to-Market Ratio (Characteristics Index–GARCH Estimation Procedure)

Table 26: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce Different Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: –LOBTM(0,+50)							
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***	**Skewness corrected *T1***
(–10, –6)	7	1.30%	4:3	0.380	0.324	0.565	0.305
(–5, –2)	7	2.12%	3:4	0.691	0.831	–0.193	1.063
(–1, +1)	7	9.86%	5:2)	3.708***	0.840	1.323$	1.083
(–3, +3)	7	9.20%	5:2)	2.267*	0.794	1.323$	0.979
(+11, +50)	7	4.46%	5:2)	0.460	1.253	1.323$	1.419$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 27: Positive High Book-to-market Ratio (Characteristics Index–OLS Estimation Procedure)

Table 27: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive, and Does Not Explain the Anomaly. Hence, Companies Time the Market

Market model: +HIBTM(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*	Skewness corrected *T1*
(–10,–6)	3	2.14%	4.70%	2:1	1.002	1.042	0.519	0.912	0.392
(–5,–2)	3	0.75%	5.61%	1:2	0.828	0.382	0.127	–0.263	0.137
(–1,+1)	3	10.49%	8.25%	3:0>	2.390**	14.340***	2.836**	2.087*	4.823***
(–3,+3)	3	10.81%	12.01%	3:0>	2.031*	1.934*	2.397**	2.087*	1.328$
(+11, +50)	3	–23.43%	–22.65%	0:3(	–1.717*	–3.982***	–8.705***	–1.438$	–14.572***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 28: Positive High Book-to-market Ratio (Characteristics Index–GARCH Estimation Procedure)

Table 28: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market. Different Estimation Procedures Produce Same Results. GARCH Is a Better Fit When Using Daily Returns Data							
Market model estimated by GARCH: +HIBTM(0,+50)							
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***	**Skewness corrected *T1***
(–10, –6)	3	2.63%	2:1	0.392	0.724	0.618	0.504
(–5, –2)	3	1.04%	1:2	0.174	0.181	–0.537	0.195
(–1, +1)	3	10.75%	3:0>	2.068*	2.712**	1.773*	4.611***
(–3, +3)	3	11.40%	3:0>	1.436$	2.325*	1.773*	1.717*
(+11, +50)	3	–19.91%	0:3<	–1.049	–5.012***	–1.692*	–4.836***
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.							

Table 29: Negative High Book-to-market Ratio (Characteristics Index–OLS Estimation Procedure)

Table 29: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Negative, and Explains the Anomaly. Hence, Companies Do Not Time the Market

Market model: –HIBTM(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	2	6.19%	3.29%	1:1	0.421	0.427	0.706	0.280
(–5, –2)	2	7.93%	5.14%	1:1	0.833	0.990	0.995	0.280
(–1, +1)	2	43.54%	32.12%	2:0>	6.022***	1.842*	1.333$	1.722*
(–3, +3)	2	39.80%	28.55%	2:0>	3.486***	1.559$	1.235	1.722*
(+11, +50)	2	–1.56%	4.70%	0:2	–0.069	–4.363***	–1.805*	–1.162

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 30: Negative High Book-to-market Ratio (Characteristics Index–GARCH Estimation Procedure)

Table 30: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce Different Results. GARCH Is a Better Fit When Using Daily Returns Data						
Market model estimated by GARCH: –HIBTM(0,+50)						
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	2	6.63%	1:1	0.787	0.735	0.226
(–5, –2)	2	8.60%	2:0>	1.141	1.060	1.659*
(–1, +1)	2	43.87%	2:0>	6.719***	1.335$	1.659*
(–3, +3)	2	40.78%	2:0>	4.089***	1.251	1.659*
(+11, +50)	2	2.84%	2:0>	0.119	9.543***	1.659*
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.						

Table 31: Positive Small (Characteristics Index–OLS Estimation Procedure)

Table 31: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive, and Does Not Explain the Anomaly. Hence, Companies Time the Market

Market model: +SMALL(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*	Skewness corrected *T1*
(–10, –6)	3	2.43%	4.77%	2:1	0.955	1.119	0.758	0.885	0.541
(–5, –2)	3	0.71%	5.66%	1:2	0.813	0.367	0.117	–0.287	0.126
(–1, +1)	3	10.65%	8.30%	3:0>	2.402**	17.393***	2.855**	2.056*	4.399***
(–3, +3)	3	10.97%	12.07%	3:0>	2.041*	1.976*	2.441**	2.056*	1.437$
(+11, +50)	3	–23.28%	–24.03%	0:3(	–1.738*	–3.676***	–5.365***	–1.459$	–18.583***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 32: Positive Small (Characteristics Index–GARCH Estimation Procedure)

Table 32: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market. Different Estimation Procedures Produce Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: +SMALL(0,+50)

Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*	Skewness corrected *T1*
(–10, –6)	3	2.60%	2:1	0.398	0.911	0.552	0.638
(–5, –2)	3	0.92%	1:2	0.157	0.153	–0.603	0.163
(–1, +1)	3	10.75%	3:0>	2.129*	2.722**	1.707*	4.383***
(–3, +3)	3	11.31%	3:0>	1.465$	2.295*	1.707*	1.683*
(+11, +50)	3	–20.60%	0:3<	–1.117	–3.786***	–1.757*	–6.205***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 33: Negative Small (Characteristics Index–OLS Estimation Procedure)

Table 33: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Insignificant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market

Market model: –SMALL(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	6	3.31%	2.82%	4:2	0.832	0.910	1.134	1.130
(–5, –2)	6	2.45%	0.77%	3:3	0.336	0.530	0.853	0.307
(–1, +1)	6	11.52%	6.98%	5:1>	2.914**	0.989	0.835	1.953*
(–3, +3)	6	10.68%	7.45%	5:1>	2.016*	1.043	0.788	1.953*
(+11, +50)	6	0.42%	1.49%	2:4	0.568	0.657	0.077	–0.516

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 34: Negative Small (Characteristics Index–GARCH Estimation Procedure)

Table 34: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce Different Results. GARCH Is A Better Fit When Using Daily Returns Data

Market model estimated by GARCH: –SMALL(0,+50)

Days	N	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) t	CSectErr t	Generalized sign Z
(–10, –6)	6	3.62%	4:2	0.903	1.219	1.024
(–5, –2)	6	3.17%	4:2	0.882	1.107	1.024
(–1, +1)	6	12.31%	5:1>	3.957***	0.908	1.843*
(–3, +3)	6	12.30%	5:1>	2.589**	0.942	1.843*
(+11, +50)	6	6.59%	5:1>	0.580	2.021*	1.843*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 35: Positive Big (Characteristics Index–OLS Estimation Procedure)

Table 35: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market

Market model: +BIG(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*	Skewness corrected *T1*
(–10, –6)	4	1.14%	2.33%	2:2	0.850	0.688	0.350	0.295	0.368
(–5, –2)	4	3.92%	7.34%	2:2	1.733*	0.896	0.739	0.295	0.706
(–1,+1)	4	6.72%	4.79%	3:1)	1.608$	1.506$	1.470$	1.305$	1.418$
(–3,+3)	4	9.44%	9.95%	4:0>	2.034*	2.313*	2.744**	2.316*	3.124***
(+11, +50)	4	–27.39%	–31.83%	0:4<	–2.614**	–3.364***	–4.518***	–1.727*	–6.217***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 36: Positive Big (Characteristics Index–GARCH Estimation Procedure)

Table 36: Shows Some cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market. Different Estimation Procedures Produce Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: +BIG(0,+50)

Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***	**Skewness Corrected *T1***
(–10, –6)	4	1.32%	2:2	0.248	0.421	0.034	0.447
(–5, –2)	4	4.14%	2:2	0.872	0.793	0.034	0.744
(–1, +1)	4	6.85%	3:1	1.665*	1.456$	1.034	1.458$
(–3, +3)	4	9.79%	4:0>	1.558$	2.597**	2.034*	3.218***
(+11, +50)	4	–25.00%	0:4<	–1.664*	–3.324***	–1.966*	–3.162***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 37: Negative Big (Characteristics Index–OLS Estimation Procedure)

Table 37: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market

Market model: –BIG(0,+50)								
Days	***N***	**Mean cumulative abnormal return**	**Precision-weighted CAAR**	**Positive: Negative**	**Patell *Z***	**StdCsect *Z***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	5	2.42%	0.58%	2:3	0.208	0.184	0.768	–0.125
(–5, –2)	5	3.09%	0.06%	2:3	0.126	0.172	0.942	–0.125
(–1, +1)	5	17.36%	9.82%	4:1>	2.549**	0.719	1.167	1.683*
(–3, +3)	5	14.74%	8.52%	3:2	1.278	0.507	1.010	0.779
(+11, +50)	5	15.41%	10.60%	4:1>	1.469$	1.613$	1.274	1.683*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 38: Negative Big (Characteristics Index–GARCH Estimation Procedure)

Table 38: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: –BIG(0,+50)						
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	5	2.69%	2:3	0.480	0.813	–0.141
(–5, –2)	5	3.53%	2:3	0.704	1.046	–0.141
(–1, +1)	5	17.59%	4:1>	4.056***	1.175	1.665*
(–3, +3)	5	15.34%	3:2	2.316*	1.042	0.762
(+11, +50)	5	19.16%	4:1>	1.210	1.413$	1.665*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 39: Positive Small-low Book-To-market Ratio (Characteristic Index–OLS Estimation Procedure)

Table 39: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market (Inconclusive)									
Market model: +SL(0,+50)									
Days	***N***	**Mean cumulative abnormal return**	**Precision-weighted CAAR**	**Positive: Negative**	**Patell *Z***	**StdCsect *Z***	**CSectErr *t***	**Generalized sign *Z***
(−10, −6)	6	1.22%	1.21%	3:3	0.626	0.631	0.572	0.245
(−5, −2)	6	0.52%	−0.27%	4:2	−0.154	−0.118	0.255	1.065
(−1, +1)	6	0.78%	0.99%	4:2	0.662	0.446	0.272	1.065
(−3, +3)	6	5.13%	5.34%	5:1>	2.319*	2.574**	2.477**	1.886*
(+11, +50)	6	16.52%	16.90%	6:0>>	2.959**	2.246*	2.637**	2.706**

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 40: Positive Small-low Book-to-market Ratio (Characteristic Index–GARCH Estimation Procedure)

Table 40: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition is a Positive. Hence, Companies Time the Market (Inconclusive). Different Estimation Procedures Produce the Same Results

Market model estimated by GARCH: +SL(0,+50)										
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**		**Portfolio time-series (CDA) *t***		**CSectErr *t***		**Generalized sign *Z***	
(–10, –6)	6	1.36%	3:3		0.527		0.640		0.241	
(–5, –2)	6	0.61%	4:2		0.263		0.296		1.061	
(–1, +1)	6	0.84%	4:2		0.419		0.289		1.061	
(–3, +3)	6	5.26%	5:1>		1.722*		2.454**		1.882*	
(+11, +50)	6	17.44%	6:0>>		2.387**		2.456**		2.702**	

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 41: Negative Small-low Book-to-market Ratio (Characteristic Index–OLS Estimation Procedure)

Table 41: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market									
Market model: –SL(0,+50)									
Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*	
(–10, –6)	3	1.69%	2.09%	1:2	0.270	0.405	0.271	–0.168	
(–5, –2)	3	4.71%	5.48%	2:1	0.795	1.130	0.798	1.021	
(–1, +1)	3	32.13%	30.08%	3:0>	5.050***	1.514$	1.416$	2.210*	
(–3,+3)	3	26.39%	27.26%	2:1	2.986**	1.321$	1.084	1.021	
(+11, +50)	3	–24.73%	–24.49%	0:3(	–1.089	–4.200***	–8.210***	–1.357$	
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.									

Table 42: Negative Small-low Book-To-market Ratio (Characteristic Index–GARCH Estimation Procedure)

Table 42: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model: –SL(0,+50)

Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	3	2.91%	1:2	0.308	0.486	–0.248
(–5, –2)	3	5.30%	2:1	0.626	0.879	0.928
(–1,+1)	3	32.48%	3:0>	4.432***	1.426$	2.105*
(–3,+3)	3	27.59%	2:1	2.465**	1.132	0.928
(+11, +50)	3	–18.56%	0:3(	–0.694	–4.997***	–1.425$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 43: Positive Host and Negative Long-term Reversal Portfolios (Characteristic Index–OLS Estimation Procedure)

Table 43: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market (Inconclusive)

Market model: +HNLTR(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(−10, −6)	9	−2.99%	−2.29%	3:6	−1.175	−1.166	−1.070	−0.724
(−5, −2)	9	−2.71%	−2.79%	3:6	−1.458$	−2.669**	−2.169*	−0.724
(−1, +1)	9	−1.82%	0.21%	5:4	0.208	0.109	−0.508	0.615
(−3, +3)	9	−5.00%	−2.45%	4:5	−1.008	−0.633	−1.147	−0.054
(+11, +50)	9	15.21%	17.19%	8:1>>	2.655**	2.240*	2.804**	2.624**

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 44: Positive Host and Negative Long-term Reversal Portfolios (Characteristic Index–GARCH Estimation Procedure)

Table 44: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market (Inconclusive). Different Estimation Procedures Produce the Same Results

Market model estimated by GARCH: +HNLTR(0,+50)						
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	9	–2.63%	3:6	–0.967	–1.037	–0.781
(–5, –2)	9	–2.14%	3:6	–0.881	–1.326$	–0.781
(–1, +1)	9	–1.64%	5:4	–0.780	–0.471	0.556
(–3, +3)	9	–4.34%	4:5	–1.349$	–1.068	–0.112
(+11, +50)	9	17.95%	8:1>>	2.336**	3.040**	2.562**

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 45: Positive Host and Negative Short-term Reversal Portfolios (Characteristic Index–OLS Estimation Procedure)

Table 45: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market

Market model: +HNSTR(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	2	–6.22%	–1.30%	1:1	–0.583	–0.380	–0.507	0.221
(–5, –2)	2	–8.29%	–11.82%	0:2	–1.447$	–1.219	–1.461$	–1.210
(–1, +1)	2	7.28%	8.08%	2:0>	1.208	1.611$	2.263*	1.652*
(–3, +3)	2	–2.48%	–3.00%	1:1	–0.068	–0.111	–0.373	0.221
(+11, +50)	2	–41.74%	–37.75%	0:2	–1.631$	–15.873***	–5.613***	–1.210

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 46: Positive Host and Negative Long-term Reversal Portfolios (Characteristic Index–GARCH Estimation Procedure)

Table 46: Shows Some Cases Where Post-listing AnomalyExists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market. Different Estimation Procedures Produce Same Results

Market model estimated by GARCH: +HNSTR(0,+50)						
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	2	–6.48%	1:1	–0.712	–0.525	0.194
(–5, –2)	2	–7.80%	0:2	–0.958	–1.294$	–1.234
(–1, +1)	2	8.46%	2:0)	1.199	4.213***	1.621$
(–3, +3)	2	–1.44%	1:1	–0.134	–0.256	0.194
(+11, +50)	2	–35.32%	0:2	–1.371$	–10.563***	–1.234

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 47: Negative Host and Negative Long-term Reversal Portfolios (Characteristic Index–OLS Estimation Procedure)

Table 47: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market

Market model: –HNLTR(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	2	3.70%	2.12%	1:1	0.586	0.928	0.969	0.381
(–5, –2)	2	2.54%	1.68%	2:0>	0.517	1.617$	1.217	1.845*
(–1, +1)	2	5.46%	4.00%	2:0>	1.425$	3.115***	1.543$	1.845*
(–3, +3)	2	7.19%	5.69%	2:0>	1.324$	8.853***	1.990*	1.845*
(+11, +50)	2	11.67%	9.01%	2:0>	0.852	5.641***	1.819*	1.845*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 48: Negative Host and Negative Long-term Reversal Portfolios (Characteristic Index–GARCH Estimation Procedure)

Table 48: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Market model estimated by GARCH: –HNLTR(0,+50)

Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	2	4.13%	2:0)	0.829	1.092	1.419$
(–5, –2)	2	2.86%	2:0)	0.641	1.386$	1.419$
(–1, +1)	2	5.69%	2:0)	1.476$	1.618$	1.419$
(–3, +3)	2	7.75%	2:0)	1.315$	2.177*	1.419$
(+11, +50)	2	14.89%	2:0)	1.057	2.438**	1.419$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 49: Negative Host and Negative Short-term Reversal Portfolios (Characteristic Index–OLS Estimation Procedure)

Table 49: Shows Some Cases Where Post-listing Anomaly Exists (Insignificant Negative Post-listing Period CAAR). Host Market Condition Is a Negative and Explains the Anomaly. Hence, Companies Do Not Time the Market

Market model: –HNSTR(0,+50)								
Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	2	–3.34%	–2.86%	1:1	–0.232	–0.387	–0.640	0.121
(–5, –2)	2	–1.81%	–0.01%	0:2(	–0.354	–1.471$	–2.344**	–1.298$
(–1, +1)	2	5.10%	2.31%	1:1	0.209	0.102	0.400	0.121
(–3, +3)	2	1.94%	–1.49%	1:1	–0.199	–0.120	0.123	0.121
(+11, +50)	2	–31.42%	–29.84%	0:2(	–1.739*	–1.310$	–1.645*	–1.298$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 50: Negative Host and Negative Short-term Reversal Portfolios (Characteristic Index–GARCH Estimation Procedure)

Table 50: Shows Some Cases Where Post-listing AnomalyExists (Insignificant Negative Post-listing Period CAAR). Host Market Condition Is a Negative and Explains the Anomaly. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Market model estimated by GARCH: –HNSTR(0,+50)

Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	2	–2.20%	1:1	–0.261	–0.510	0.006
(–5, –2)	2	–1.36%	0:2(	–0.181	–1.082	–1.409$
(–1, +1)	2	5.60%	1:1	0.859	0.430	0.006
(–3, +3)	2	3.04%	1:1	0.306	0.183	0.006
(+11, +50)	2	–26.55%	0:2(	–1.116	–1.170	–1.409$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 51: Positive Host and Positive Momentum Portfolios (Characteristic Index–OLS Estimation Procedure)

Table 51: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market

Market model: +HPMOM(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*	Skewness corrected *T1*
(–10, –6)	5	–1.64%	1.71%	1:4	0.263	0.243	–0.537	–1.088	–0.516
(–5, –2)	5	–0.24%	1.97%	1:4	0.530	0.364	–0.082	–1.088	–0.086
(–1, +1)	5	5.47%	3.32%	4:1)	1.078	0.879	1.387$	1.613$	1.495$
(–3, +3)	5	1.84%	3.09%	2:3	0.560	0.394	0.323	–0.188	0.342
(+11, +50)	5	–42.96%	–39.70%	0:5<	–3.915***	–1.787*	–1.746*	–1.989*	–2.804**

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 52: Positive Host and Positive Momentum Portfolios (Characteristic Index–GARCH Estimation Procedure)

Table 52: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive. Hence, Companies Time the Market. Different Estimation Procedures Produce the Same Results

Market model estimated by GARCH: +HPMOM(0,+50)							
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***	**Skewness corrected *T1***
(−10, −6)	5	−2.03%	1:4	−0.322	−0.586	−1.195	−0.581
(−5, −2)	5	−0.31%	1:4	−0.056	−0.104	−1.195	−0.107
(−1, +1)	5	5.81%	4:1)	1.189	1.403$	1.494$	1.500$
(−3, +3)	5	1.93%	2:3	0.259	0.317	−0.298	0.337
(+11, +50)	5	−42.48%	0:5<	−2.381**	−1.680*	−2.091*	−2.574**

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 53: Negative Host and Positive Momentum Portfolios (Characteristic Index–OLS Estimation Procedure)

Table 53: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Negative and Explains the Anomaly. Hence, Companies Do Not Time the Market

Market model: –HPMOM(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision -weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	2	–20.43%	–14.22%	0:2	–1.957*	–1.315$	–1.139	–1.270
(–5, –2)	2	3.91%	5.91%	1:1	0.924	0.826	0.673	0.152
(–1, +1)	2	–0.57%	–3.16%	1:1	–0.379	–0.348	–0.104	0.152
(–3, +3)	2	–8.19%	–5.29%	1:1	–0.596	–0.627	–0.785	0.152
(+11, +50)	2	–61.70%	–51.81%	0:2	–2.668**	–5.576***	–2.164*	–1.270

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 54: Negative Host and Positive Momentum Portfolios (Characteristic Index–GARCH Estimation Procedure)

Table 54: Shows some cases where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition is a Negative and Explains the Anomaly. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Market model: –HPMOM(0,+50)						
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	2	–15.82%	0:2(	–1.718*	–1.145	–1.310$
(–5, –2)	2	4.51%	1:1	0.547	0.811	0.108
(–1, +1)	2	–0.36%	1:1	–0.050	–0.066	0.108
(–3, +3)	2	–5.05%	1:1	–0.463	–0.630	0.108
(+11, +50)	2	–47.98%	0:2(	–1.842*	–2.607**	–1.310$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 55: Positive Sentiment Index (Market Index–OLS Estimation Procedure)

Table 55: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market

Market model: +SENT(0,+50)

Days	***N***	**Mean cumulative abnormal return**	**Precision -weighted CAAR**	**Positive: Negative**	**Patell *Z***	**StdCsect *Z***	**CSectErr *t***	**Generalized sign *Z***	**Skewness corrected *T1***
(–10, –6)	4	1.72%	2.50%	3:1)	0.563	1.150	0.559	1.334$	0.509
(–5, –2)	4	–7.48%	–7.28%	0:4<	–1.830*	–1.932*	–1.814*	–1.704*	–2.860**
(–1, +1)	4	1.76%	–0.96%	2:2	–0.275	–0.192	0.330	0.322	0.328
(–3, +3)	4	–6.24%	–6.75%	0:4<	–1.267	–2.025*	–2.118*	–1.704*	–2.967**
(+11, +50)	4	–39.66%	–40.20%	1:3	–2.999**	–1.392$	–1.300$	–0.691	–1.813*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 56: Positive Sentiment Index (Market Index–GARCH Estimation Procedure)

Table 56: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market. Different Estimation Procedures Produce the Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: +SENT(0,+50)							
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*	Skewness corrected *T1*
(−10, −6)	4	1.73%	3:1)	0.263	0.545	1.330$	0.506
(−5, −2)	4	−7.47%	0:4<	−1.269	−1.815*	−1.707*	−2.891**
(−1, +1)	4	1.77%	2:2	0.348	0.334	0.318	0.332
(−3,+3)	4	−6.25%	0:4<	−0.803	−2.245*	−1.707*	−3.031**
(+11, +50)	4	−40.87%	0:4<	−2.196*	−1.358$	−1.707*	−1.918*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 57: Negative Sentiment Index (Market Index–OLS Estimation Procedure)

Table 57: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market								
Market model: –SENT(0,+50)								
Days	**N**	**Mean cumulative abnormal return**	**Precision - weighted CAAR**	**Positive: Negative**	**Patell Z**	**StdCsect Z**	**CSectErr t**	**Generalized sign Z**
(–10, –6)	16	0.32%	0.10%	9:7	0.073	0.060	0.194	0.826
(–5, –2)	16	–1.15%	–1.45%	7:9	–1.233	–1.435$	–1.065	–0.177
(–1, +1)	16	0.64%	0.28%	10:6)	0.280	0.221	0.497	1.328$
(–3, +3)	16	–0.39%	–0.15%	8:8	–0.083	–0.059	–0.174	0.325
(+11, +50)	16	18.97%	13.55%	11:5>	3.403***	3.001**	2.764**	1.829*
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.								

Table 58: Negative Sentiment Index (Market Index–GARCH Estimation Procedure)

Table 58: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce Same Results GARCH Is a Better Fit When Using Daily Returns Data						
Market model estimated by GARCH: –SENT(0,+50)						
Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	16	0.32%	10:6)	0.145	0.205	1.291$
(–5, –2)	16	–1.13%	7:9	–0.572	–0.988	–0.213
(–1, +1)	16	0.66%	10:6)	0.388	0.502	1.291$
(–3, +3)	16	–0.33%	10:6)	–0.126	–0.141	1.291$
(+11, +50)	16	17.88%	11:5>	2.859**	2.967**	1.792*
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.						

Table 59: Positive Momentum Index (Market Index–OLS Estimation Procedure)

Table 59: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market									
Market model: +MOM(0,+50)									
Days	***N***	**Mean cumulative abnormal return**	**Precision-weighted CAAR**	**Positive: Negative**	**Patell *Z***	**StdCsect *Z***	**CSectErr *t***	**Generalized sign *Z***	**Skewness corrected *T1***
(–10, –6)	6	–1.21%	1.58%	2:4	0.303	0.313	–0.477	–0.536	–0.468
(–5, –2)	6	–1.06%	1.05%	1:5(	0.143	0.104	–0.421	–1.358$	–0.396
(–1, +1)	6	6.30%	4.40%	5:1>	1.548$	1.339$	1.895*	1.930*	1.840*
(–3,+3)	6	3.69%	4.73%	3:3	1.048	0.781	0.736	0.286	0.748
(+11, +50)	6	–41.83%	–39.43%	0:6<	–4.088***	–2.075*	–2.079*	–2.180*	–3.590***
The symbols $, *, **, and *** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.									

Table 60: Positive Momentum Index (Market Index–GARCH Estimation Procedure)

Table 60: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market. Different Estimation Procedures Produce the Same Results. GARCH Is A Better Fit When Using Daily Returns Data

Market model estimated by GARCH: +MOM(0,+50)

Days	*N*	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***	**Skewness corrected *T1***
(–10, –6)	6	–1.53%	2:4	–0.276	–0.532	–0.640	–0.536
(–5, –2)	6	–1.12%	1:5(	–0.225	–0.431	–1.459$	–0.407
(–1, +1)	6	6.59%	5:1>	1.536$	1.900*	1.816*	1.843*
(–3, +3)	6	3.78%	3:3	0.576	0.712	0.178	0.730
(+11, +50)	6	–41.28%	0:6<	–2.634**	–1.995*	–2.278*	–3.273***

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 61: Negative Momentum Index (Market Index–OLS Estimation Procedure)

Days	N	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell Z	StdCsect Z	CSectErr t	Generalized sign Z
Table 61: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market								
Market model: –MOM(0,+50)								
(–10, –6)	8	1.19%	0.95%	5:3	0.522	0.642	0.808	0.846
(–5, –2)	8	–0.82%	–0.44%	3:5	–0.297	–0.385	–0.639	–0.570
(–1,+1)	8	–2.08%	–1.45%	3:5	–1.132	–0.942	–1.152	–0.570
(–3,+3)	8	–4.40%	–2.58%	3:5	–1.306$	–0.903	–1.229	–0.570
(+11, +50)	8	11.22%	11.33%	7:1>	2.338**	2.471**	2.612**	2.262*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 62: Negative Momentum Index (Market Index–GARCH Estimation Procedure)

Table 62: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce Different Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: –MOM(0,+50)							
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***	
(–10, –6)	8	1.15%	5:3	0.631	0.796	0.868	
(–5, –2)	8	–0.85%	3:5	–0.523	–0.657	–0.548	
(–1, +1)	8	–2.07%	4:4	–1.465$	–1.131	0.160	
(–3, +3)	8	–4.42%	4:4	–2.046*	–1.218	0.160	
(+11, +50)	8	10.56%	7:1>	2.046*	2.574**	2.285*	

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 63: Positive LTR Index (Market Index–OLS Estimation Procedure)

Table 63: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market								
Market model: +LTR(0,+50)								
Days	***N***	**Mean cumulative abnormal return**	**Precision-weighted CAAR**	**Positive: Negative**	**Patell *Z***	**StdCsect *Z***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	2	8.70%	8.17%	2:0)	1.817*	6.691***	5.174***	1.533$
(–5, –2)	2	6.29%	8.82%	1:1	2.098*	0.994	0.989	0.114
(–1, +1)	2	–1.51%	0.52%	1:1	0.147	0.091	–0.248	0.114
(–3, +3)	2	3.40%	6.86%	1:1	1.120	0.512	0.348	0.114
(+11, +50)	2	–45.61%	–36.45%	0:2(	–2.767**	–2.281*	–1.503$	–1.305$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 64: Positive LTR Index (Market Index–GARCH Estimation Procedure)

Table 64: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market. Different Estimation Procedures Produce the Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: +LTR(0,+50)

Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	2	8.85%	2:0)	1.654*	4.732***	1.527$
(–5, –2)	2	6.37%	2:0)	1.332$	1.021	1.527$
(–1, +1)	2	–1.43%	1:1	–0.344	–0.238	0.109
(–3, +3)	2	3.50%	1:1	0.554	0.364	0.109
(+11, +50)	2	–44.73%	0:2(	–2.957**	–1.536$	–1.310$

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 65: Positive STR Index (Market Index–OLS Estimation Procedure)

Table 65: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market

Market model: +STR(0,+50)								
Days	*N*	**Mean cumulative abnormal return**	**Precision-weighted CAAR**	**Positive: Negative**	**Patell *Z***	**StdCsect *Z***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	4	–1.20%	2.74%	3:1	0.378	0.295	–0.202	1.212
(–5, –2)	4	0.07%	3.98%	2:2	0.760	0.370	0.012	0.207
(–1, +1)	4	7.45%	7.20%	4:0>	2.270*	4.168***	4.292***	2.217*
(–3, +3)	4	5.80%	9.67%	3:1	1.858*	1.469$	1.055	1.212
(+11, +50)	4	–29.19%	–25.02%	0:4<	–2.063*	–9.447***	–3.704***	–1.804*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 66: Positive STR Index (Market Index–GARCH Estimation Procedure)

Table 66: Shows Some Cases Where Post-listing Anomaly Exists (Significant Negative Post-listing Period CAAR). Host Market Condition Is a Positive and Does Not Explain the Anomaly. Hence, Companies Time the Market. Different Estimation Procedures Produce the Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: +STR(0,+50)

Days	*N*	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	4	–1.33%	3:1	–0.261	–0.221	1.192
(–5, –2)	4	0.32%	2:2	0.071	0.057	0.188
(–1, +1)	4	8.05%	4:0>	2.047*	5.661***	2.196*
(–3, +3)	4	6.34%	3:1	1.055	1.256	1.192
(+11, +50)	4	–25.89%	0:4<	–1.803*	–4.592***	–1.821*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 67: Negative LTR Index (Market Index–OLS Estimation Procedure)

Table 67: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market

Market model: –LTR(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	11	–0.58%	–0.63%	4:7	–0.345	–0.322	–0.221	–0.545
(–5, –2)	11	1.73%	0.86%	8:3>	0.480	0.526	0.877	1.881*
(–1,+1)	11	6.02%	2.89%	7:4	2.062*	0.840	0.792	1.275
(–3,+3)	11	6.39%	3.98%	7:4	1.747*	1.019	0.861	1.275
(+11, +50)	11	4.88%	8.13%	8:3>	1.540$	1.975*	0.865	1.881*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 68: Negative LTR Index (Market Index–GARCH Estimation Procedure)

Table 68: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce Different Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: –LTR(0,+50)

Days	*N*	Mean cumulative abnormal return	Positive: Negative	Portfolio time-series (CDA) *t*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	11	–0.53%	5:6	–0.211	–0.196	–0.116
(–5, –2)	11	1.81%	7:4	0.809	0.884	1.092
(–1, +1)	11	6.17%	7:4	3.179***	0.811	1.092
(–3, +3)	11	6.74%	7:4	2.272*	0.901	1.092
(+11, +50)	11	6.44%	9:2>	0.909	1.392$	2.300*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 69: Negative STR Index (Market Index–OLS Estimation Procedure)

Table 69: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market

Market model: –STR(0,+50)

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	6	2.63%	0.47%	4:2	0.208	0.162	0.818	1.089
(–5, –2)	6	3.66%	0.84%	4:2	0.416	0.545	1.253	1.089
(–1, +1)	6	15.82%	5.99%	5:1>	3.445***	1.197	1.288$	1.910*
(–3, +3)	6	16.65%	6.79%	5:1>	2.547**	1.188	1.411$	1.910*
(+11, +50)	6	16.24%	11.00%	4:2	1.559$	2.017*	1.791*	1.089

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 70: Negative STR Index (Market Index–GARCH Estimation Procedure)

Table 70: Shows Some Cases Where Post-listing Anomaly Does Not Exist (Significant Positive Post-listing Period CAAR). Host Market Condition Is a Negative. Hence, Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results. GARCH Is a Better Fit When Using Daily Returns Data

Market model estimated by GARCH: –STR(0,+50)						
Days	***N***	**Mean cumulative abnormal return**	**Positive: Negative**	**Portfolio time-series (CDA) *t***	**CSectErr *t***	**Generalized sign *Z***
(–10, –6)	6	2.85%	4:2	0.653	0.867	1.104
(–5, –2)	6	4.15%	4:2	1.063	1.369$	1.104
(–1, +1)	6	16.00%	5:1>	4.734***	1.292$	1.926*
(–3, +3)	6	17.30%	5:1>	3.351***	1.447$	1.926*
(+11, +50)	6	19.00%	5:1>	1.540$	1.887*	1.926*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 71: Portfolios Formed on Market Timers

Table 71: Post-listing Anomaly Exists (Significant Negative CAAR in The Post-listing Period)

Market model: +DJIA(0,+50) Market timers

Days	N	Mean cumulativ e abnormal return	Precision-weighted CAAR	Positive: Negative	Patell Z	StdCsect Z	CSectErr t	Generalized sign Z
(–10, –6)	10	–1.52%	0.28%	4:6	0.113	0.159	–0.680	–0.306
(–5, –2)	10	–1.02%	0.64%	3:7	0.280	0.198	–0.361	–0.942
(–1, +1)	10	3.77%	2.53%	7:3)	1.279	1.079	1.425$	1.602$
(–3, +3)	10	1.48%	2.72%	5:5	0.898	0.764	0.407	0.330
(+11, +50)	10	–29.82%	–26.92%	0:10<<	–3.576***	–3.116***	–2.994**	–2.849**

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 72: Portfolios Formed on Non-market Timers

Table 72: Post-listing Anomaly Does Not Exist (Significant Positive CAAR in the Post-listing Period)

Market model: –DJIA(0,+50) Non-market timers

Days	*N*	Mean cumulative abnormal return	Precision-weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	CSectErr *t*	Generalized sign *Z*
(–10, –6)	22	–0.57%	–0.46%	11:11	–0.382	–0.434	–0.386	0.460
(–5, –2)	22	–0.44%	–1.15%	12:10	–1.102	–1.225	–0.381	0.889
(–1, +1)	22	3.67%	1.66%	14:8>	1.826*	0.934	0.953	1.746*
(–3, +3)	22	2.51%	1.35%	13:9)	0.974	0.575	0.617	1.317$
(+11, +50)	22	8.12%	8.50%	14:8>	2.459**	2.536**	2.054*	1.746*

The symbols $, *, **, and * denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> correspond to $, * and show the direction and generic one-tail significance of the generalized sign test.**

Table 73: Difference in Means between Market Timers and Non-market Timers (Parametric)

Table 73: Panel A							
TIMING	**Method**	**Mean**	**95% CL**	**Mean**	**Std. dev.**	**95% CL**	**Std. dev.**
NOTIMERS		–0.0360	–0.0375	–0.0345	0.1200	0.1189	0.1211
Dtimers		0.000433	–0.00205	0.00292	0.1396	0.1379	0.1414
Diff (1–2)	**Pooled**	–0.0365*	–0.0392	–0.0337	0.1268	0.1259	0.1277
Diff (1–2)	**Satterthwaite**	–0.0365*	–0.0394	–0.0336			

Table 73: Panel B				
		Equality of variances		
Method	**Num DF**	**Den DF**	***F*-value**	**Pr > F**
Folded F	12,129	24,751	1.35	<.0001

Table 74: Difference in Means between Market Timers and Non-market Timers (Non-parametric)

Table 74: Panel A					
Wilcoxon scores (rank sums) for variable ABS_DISCACCR Classified by variable TIMING					
TIMING	***N***	**Sum of scores**	**Expected under H0**	**Std. dev. under H0**	**Mean score**
NOTIMERS	24,752	410,706,937	456,464,008	960,611.657	16,592.8788
Dtimers	12,130	269,452,466	223,695,395	960,611.657	22,213.7235
Average scores were used for ties					

Table 74: Panel B	
Wilcoxon two-sample test	
Statistic	269,452,466.0000
Normal approximation	
Z	47.6333
One-sided Pr >*Z*	<.0001
Two-sided Pr > |*Z*|	<.0001
***t* approximation**	
One-sided Pr >*Z*	<.0001
Two-sided Pr > |*Z*|	<.0001
Z includes a continuity correction of 0.5	

Table 75: Difference in Medians between Market Timers and Non-market Timers (Non-parametric)

Table 75: Panel A					
Median scores (Number of points above median) for variable ABS_DISCACCR Classified by variable TIMING					
TIMING	***N***	**Sum of scores**	**Expected under H0**	**Std. dev. under H0**	**Mean score**
NOTIMERS	24,752	11,377.0	12,376.0	44.954116	0.459640
Dtimers	12,130	7,064.0	6,065.0	44.954116	0.582358
Average scores were used for ties					

Table 75: Panel B	
Median two-sample test	
Statistic	7,064.0000
Z	22.2227
One-sided Pr >*Z*	<.0001
Two-sided Pr > |*Z*|	<.0001

Table 76: Correlation Coefficients between Independent Variables

Table 76: Show Pearson correlation coefficients					
	Pearson correlation coefficients Prob > |r| under H0: Rho = 0 Number of observations				
	Size	**BMR**	**ROA**	**LEV**	**Timers**
BMR Book-to-market ratio	–0.14708* <.0001				
ROA Return on assets	0.40664* <.0001	–0.07429* <.0001			
LEV Leverage	0.24904* <.0001	–0.07600* <.0001	0.16105* <.0001		
DTIMERS Dtimers	–0.28807* <.0001	0.15636* <.0001	–0.38431* <.0001	–0.30526* <.0001	

* Significant at the 5% level.

Table 77: Regression Diagnostic for the Model

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BM$$

Table 77: Panel A						
			Analysis of variance			
Source		**DF**	**Sum of squares**	**Mean square**	***F*-value**	**Pr > *F***
Model		5	120.782	24.157	3,763.77	<.0001
Error		36,616	235.005	0.0064		
Corrected total		36,621	355.787			
Root MSE	0.08011				R-Square	0.3395
Dependent mean	0.08781				Adj R-Sq	0.3394
Coeff. var.	91.23665					

Table 77: Panel B									
				Parameter Estimates					
Variable	**Label**	**DF**	**Parameter estimate**	**Standard error**	***t*-value**	**Pr > |*t*|**	**Standardized estimate**	**Tolerance**	**Variance inflation**
Intercept	Intercept	1	0.12851*	0.00156	82.34	<.0001	0	0	0
ROA	Return on assets	1	−0.24136*	0.00244	−98.81	<.0001	−0.48533	0.74775	1.33735
Size	Size	1	−0.00529*	0.00023948	−22.09	<.0001	−0.10650	0.77624	1.28826
BMR	Book-to-market ratio	1	−0.00228*	0.00027850	−8.18	<.0001	−0.03540	0.96344	1.03794
LEV	Leverage	1	−0.00345*	0.00025643	−13.46	<.0001	−0.06110	0.87515	1.14266
DTIMERS	Dtimers	1	**0.01417***	**0.00101**	**13.97**	**<.0001**	**0.06764**	**0.76913**	**1.30017**

Table 77 (cont.): Regression Diagnostic for the Model

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BM$$

Table 77: Panel C

Collinearity diagnostics (intercept adjusted)

			Proportion of variation				
Number	**Eigenvalue**	**Condition index**	**ROA**	**Size**	**BMR**	**LEV**	**TIMERS**
1	**1.96886**	**1.00000**	0.09848	0.10222	0.02617	0.07096	0.10480
2	**0.95588**	**1.43518**	0.04718	0.00439	0.92943	0.01006	0.00094017
3	**0.86535**	**1.50838**	0.20078	0.06213	0.00268	0.68991	0.01225
4	**0.70380**	**1.67257**	0.02143	0.48719	0.00029752	0.06509	0.53061
5	**0.50611**	**1.97236**	0.63212	0.34407	0.04142	0.16397	0.35140

Table 77: Panel D

Test of first and second moment specification

DF	**Chi-Square**	**Pr > Chi-Sq**
19	5,012.32	<.0001

Table 78: Robust Standard Error Regression Model

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BMR$$

Table 78: Panel A

Analysis of variance					
Source	**DF**	**Sum of squares**	**Mean square**	***F*-value**	**Pr > *F***
Model	5	120.781	24.156	3,763.77	<.0001
Error	36,616	235.005	0.006		
Corrected total	36,621	355.786			

Root MSE	0.080	**R-Square**	0.340
Dependent mean	0.088	**Adj R-Sq**	0.339
Coeff. var.	91.237		

Table 78: Panel B

Parameter estimates							Heteroscedasticity consistent		
Variable	**Label**	**DF**	**Parameter estimate**	**Standard error**	***t*-value**	**Pr > |*t*|**	**Standard error**	***t*-value**	**Pr > |*t*|**
Intercept	Intercept	1	0.12851*	0.00156	82.34	<.0001	0.00126	101.96	<.0001
ROA	Return on assets	1	–0.24136*	0.00244	–98.81	<.0001	0.00528	–45.71	<.0001
Size	Size	1	–0.00529*	0.00023948	–22.09	<.0001	0.00017462	–30.30	<.0001
BMR	Book-to-market	1	–0.00228*	0.00027850	–8.18	<.0001	0.00010980	–20.75	<.0001
LEV	Lever	1	–0.00345*	0.00025643	–13.46	<.0001	0.00020667	–16.70	<.0001
DTIMERS	Timers	1	**0.01417***	**0.00101**	**13.97**	**<.0001**	**0.00075443**	**18.78**	**<.0001**

Table 78 (cont.): Robust Standard Error Regression Model

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BMR$$

Table 78: Panel C

Variable	Parameter estimate	Standard error	*t*-value	Pr > |*t*|	ROBUST_STDERR	TVALUE_RB	PROBT_RB
Intercept	0.12851*	0.00156	82.34	<.0001	0.001268	101.3077	0
ROA	–0.24136*	0.00244	–98.81	<.0001	0.005314	–45.4211	0
Size	–0.00529*	0.00023948	–22.09	<.0001	0.000176	–30.1062	0
BMR	–0.00228*	0.00027850	–8.18	<.0001	0.00011	–20.6214	0
LEV	–0.00345*	0.00025643	–13.46	<.0001	0.000208	–16.5904	0
DTIMERS	**0.01417***	**0.00101**	**13.97**	**<.0001**	**0.000759**	**18.65788**	**0**

Table 79: Regression Model to Determine if ROA Is Endogenous

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BMR_{i,t} + V_{i,t}$$

Table 79: Panel A

Analysis of variance					
Source	**DF**	**Sum of squares**	**Mean square**	***F*-value**	**Pr > *F***
Model	6	127.461	21.244	3,406.69	<.0001
Error	36,615	228.325	0.006		
Corrected total	36,621	355.786			
Root MSE	0.079			**R-Square**	0.358
Dependent mean	0.088			**Adj R-Sq**	0.358
Coeff. var.	89.932				

Table 79: Panel B

Parameter estimates						
Variable	**Label**	**DF**	**Parameter estimate**	**Standard error**	***t*-value**	**Pr > |*t*|**
Intercept	Intercept	1	0.09801	0.00180	54.50	<.0001
ROA	Return on assets	1	–0.39345	0.00523	–75.18	<.0001
BMR	Book-to-market ratio	1	–0.00244	0.00027456	–8.87	<.0001
LEV	Leverage	1	–0.00258	0.00025415	–10.15	<.0001
Size	Size	1	0.00065604	0.00029789	2.20	0.0276
DTIMERS	Firms that time the market	1	**0.01215***	0.00100	**12.13**	**<.0001**
V	Residual	1	**0.18811***	0. 00575	**32.73**	**<.0001**

Table 80: Regression Model using Instrumental Variable Method

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BMR_{i,t}$$

Table 80: Panel A

Analysis of Variance					
Source	**DF**	**Sum of squares**	**Mean square**	***F*-value**	**Pr > *F***
Model	5	89.948	17.990	2,515.08	<.0001
Error	36,616	261.901	0.007		
Corrected total	36,621	355.786			
Root MSE	0.0846			**R-Square**	0.25564
Dependent mean	0.0888			**Adj R-Sq**	0.25554
Coeff. var.	96.316				

Table 80: Panel B

Parameter Estimates						
Variable	**DF**	**Parameter estimate**	**Standard error**	***t*-value**	**Pr > |*t*|**	**Variable label**
Intercept	1	0.088784	0.001922	46.19	<.0001	Intercept
ROA	1	–0.37347	0.005598	–66.71	<.0001	Return on assets
Size	1	0.000818	0.000319	2.57	0.0103	Size
BMR	1	–0.00305	0.000294	–10.38	<.0001	Book-to-market ratio
LEV	1	–0.00141	0.000272	–5.17	<.0001	Leverage
DTIMERS	**1**	**0.031733***	**0.001038**	**30.57**	**<.0001**	**Firms that time the market**

Table 81: Testing for Heteroscedasticity in the Regression Model

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BMR_{i,t}$$

Table 81: Panel A							
			The equation to estimate is				
ABS_DISCACCR =	F(Const(1), C_Timers(TIMERS), C_BMR(BMR), C_Size(Size), C_LEV(LEV), C_ROA(ROA))						
			Non-linear OLS summary of residual errors				
Equation	**DF model**	**DF error**	**SSE**	**MSE**	**Root MSE**	**R-Square**	**Adj R-Sq**
ABS_DISCACCR	6	36,616	235.0	0.00642	0.0801	0.3395	0.3394

Table 81: Panel B				
		Non-linear OLS Parameter Estimates		
Parameter	**Estimate**	**Approx Std Err**	***t*-value**	**Approx Pr > |*t*|**
Const	0.128506	0.00156	82.34	<.0001
C_Timers	**0.014166***	**0.00101**	**13.97**	**<.0001**
C_BMr1	–0.00228	0.000278	–8.18	<.0001
C_Size	–0.00529	0.000239	–22.09	<.0001
C_lev3	–0.00345	0.000256	–13.46	<.0001
C_ROA	–0.24136	0.00244	–98.81	<.0001

Table 81: Panel C					
		Heteroscedasticity test			
Equation	**Test**	**Statistic**	**DF**	**Pr > Chi-Sq**	**Variables**
ABS_DISCACCR	**White's test**	**20,124***	**19**	**<.0001**	**Cross of all vars.**
	Breusch-Pagan	**5,713***	**2**	**<.0001**	**1, TIMERS, ROA**

Table 82: Using WLS to Estimate the Regression Model

Weight: 1/ROA²

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BMR_{i,t}$$

Table 82: Panel A					
		Analysis of Variance			
Source	**DF**	**Sum of squares**	**Mean square**	***F*-value**	**Pr > *F***
Model	5	2,414.808	482.96164	595.16	<.0001
Error	35,379	28,710	0.81148		
Corrected total	35,384	31,124			
Root MSE	0.901			**R-Square**	0.0776
Dependent mean	0.055			**Adj R-Sq**	0.0775
Coeff. var.	1,642.588				

Table 82: Panel B						
			Parameter estimates			
Variable	**Label**	**DF**	**Parameter estimate**	**Standard error**	***t*-value**	**Pr > |*t*|**
Intercept	Intercept	1	0.06214	0.00110	56.70	<.0001
ROA	ROA	1	–0.15439	0.00556	–27.76	<.0001
Size	Size	1	0.00030846	0.00017545	1.76	0.0787
BMR	Book–to-market ratio	1	0.05804	0.00231	25.17	<.0001
LEV	Leverage	1	–0.00086600	0.00003305	–26.20	<.0001
DTIMERS	**Market timers**	**1**	**0.00125***	**0.00061595**	**2.03**	**0.0427**

Table 83: Using FGLS to Estimate the Regression Model

Weight: 1/exp (pred)

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BMR_{i,t}$$

Table 83: Panel A

		Analysis of variance			
Source	DF	Sum of squares	Mean square	*F*-value	Pr > *F*
Model	5	80,699	16,140	2,802.76	<.0001
Error	36,616	210,853	5.7590		
Corrected total	36,621	291,552			
Root MSE	2.400			**R-Square**	0.2768
Dependent mean	0.074			**Adj R-Sq**	0.2767
Coeff. var.	3,261.061				

Table 83: Panel B

			Parameter estimates			
Variable	Label	DF	Parameter estimate	Standard error	*t*-value	Pr > |*t*|
Intercept	Intercept	1	0.11606	0.00121	96.22	<.0001
ROA	ROA	1	–0.25340	0.00277	–91.53	<.0001
Size	Size	1	–0.00410	0.00018336	–22.38	<.0001
BMR1	Book–to-market ratio	1	–0.00090014	0.00019561	–4.60	<.0001
LEV3	Leverage	1	–0.00429	0.00018128	–23.64	<.0001
DTIMERS	**Market timers**	**1**	**0.00455***	**0.00076798**	**5.93**	**<.0001**

Table 84: Testing for ARCH Process

Table 84: Panel A			
	Dependent Variable: ABS_DISCACCR		
	Ordinary least squares estimates		
SSE	235.004831	**DFE**	36,616
MSE	0.00642	**Root MSE**	0.08011
SBC	–80,905.309	**AIC**	–80,956.36
MAE	0.10608957	**AICC**	–80,956.357
MAPE	218.838355	**Regress R-Square**	0.3395
Durbin-Watson	0.0092	**Total R-Square**	0.3395

Table 84: Panel B				
		Q and LM tests for ARCH disturbances		
Order	***Q***	**Pr >*Q***	***LM***	**Pr > *LM***
1	36,372.3658	<.0001	36,369.4682	<.0001
2	72,476.2990	<.0001	36,369.8127	<.0001
3	108,303.444	<.0001	36,369.9071	<.0001
4	143,854.788	<.0001	36,369.9072	<.0001
5	179,131.312	<.0001	36,369.9081	<.0001
6	214,134.005	<.0001	36,369.9092	<.0001
7	248,863.854	<.0001	36,369.9102	<.0001
8	283,321.849	<.0001	36,369.9113	<.0001
9	317,508.983	<.0001	36,369.9124	<.0001
10	351,426.247	<.0001	36,369.9135	<.0001
11	385,096.003	<.0001	36,370.3608	<.0001
12	**418,520.259**	**<.0001**	**36,370.3624**	**<.0001**

Table 85: Testing for GARCH Process

Table 85: Panel A			
	GARCH Estimates		
SSE	284.877537	**Observations**	36,622
MSE	0.00778	**Uncond. var.**	0
Log likelihood	86,178.4265	**Total R-Square**	0.1993
SBC	−172,272.79	**AIC**	−172,340.85
MAE	0.05469041	**AICC**	−172,340.85
MAPE	142.412449	**Normality test**	7,740,334.60
		Pr > Chi-Sq	<.0001

Table 85: Panel B						
Variable	**DF**	**Estimate**	**Standard error**	***t*-value**	**Approx Pr > |*t*|**	**Variable label**
Intercept	1	0.0182	3.9618E-6	4,605.27	<.0001	
ROA	1	−0.2393	0.0000108	−22,057	<.0001	Return on assets
Size	1	0.007698	4.5288E-7	16,998.1	<.0001	Size
BMR	1	−0.000328	7.984E-7	−411.02	<.0001	Book-to-market ratio
LEV	1	−0.006607	1.3289E-6	−4,972.2	<.0001	Leverage
DTIMERS	**1**	**0.0312***	**4.4822E-6**	**6,970.89**	**<.0001**	**Firms that time the market**
ARCH0	1	1.3526E-8	1.324E-10	102.16	**<.0001**	
ARCH1	1	0.7047	0.001986	354.84	**<.0001**	
GARCH1	1	0.3680	0.001033	356.42	**<.0001**	

Table 86: Using ARCH (7) and GARCH (2) to Estimate the Regression Model

$$|ADISCACCR_{i,t}| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + LEV_{i,t} + BMR_{i,t}$$

Table 86: Panel A			
	Dependent Variable: ABS_DISCACCR		
	GARCH Estimates		
SSE	264.941684	**Observations**	36,622
MSE	0.00723	**Uncond. var.**	0
Log likelihood	82,649.2277	**Total R-Square**	0.2553
SBC	−165,130.32	**AIC**	−165,266.46
MAE	0.0524512	**AICC**	−165,266.44
MAPE	141.261797	**Normality test**	1,336,449.30
		Pr > Chi-Sq	<.0001

Table 86: Panel B						
Variable	**DF**	**Estimate**	**Standard error**	***t*-value**	**Approx Pr > |*t*|**	**Variable label**
Intercept	1	0.0536	9.1858E-6	5,838.69	<.0001	
ROA	1	−0.2528	0.0000149	−17,009	<.0001	Return on assets
Size	1	0.003326	1.6314E-6	2,038.93	<.0001	Size
BMR1	1	−0.001409	8.0052E-6	−175.98	<.0001	Book-to-market ratio
LEV3	1	−0.006267	9.0502E-7	−6,924.6	<.0001	Leverage
DTIMERS	**1**	**0.0174***	**7.17E-6**	**2,425.31**	**<.0001**	**Firms that time the market**
ARCH0	1	3.1349E-7	5.2502E-9	59.71	<.0001	
ARCH1	1	0.2197	0.002895	75.89	<.0001	
ARCH2	1	0.1628	0.008250	19.74	<.0001	
ARCH3	1	0.1530	0.0800	1.91	0.0557	
ARCH4	**1**	**0.1496**	**0.1065**	**1.40**	**0.1601**	
ARCH5	1	0.1467	0.1064	1.38	0.1679	
ARCH6	1	0.1441	0.0904	1.59	0.1112	
ARCH7	1	0.1404	0.0536	2.62	0.0088	
GARCH1	1	0.0107	0.0155	0.69	0.4911	
GARCH2	**1**	**−0.000024**	**0.000672**	**−0.04**	**0.9713**	

Table 87: Testing for Auto Correlation

Table 87: Panel A			
	Dependent variable: ***ABS_ DISCACCR***		
	OLS Estimates		
SSE	235.004831	**DFE**	36,616
MSE	0.00642	**Root MSE**	0.08011
SBC	–80,905.309	**AIC**	–80,956.36
MAE	0.05304478	**AICC**	–80,956.357
MAPE	218.838355	**Regress R-Square**	0.3395
Durbin-Watson	0.0092	**Total R-Square**	0.3395

Table 87: Panel B			
		Durbin-Watson statistics	
Order	***DW***	**Pr < *DW***	**Pr > *DW***
1	**0.0092**	**<.0001**	**1.0000**

Table 87: Panel C		
	Godfrey's serial correlation test	
Alternative	***LM***	**Pr > *LM***
AR(1)	36,286.2528	**<.0001**
AR(2)	36,286.3166	**<.0001**
AR(3)	36,286.3345	**<.0001**
AR(4)	36,286.3363	**<.0001**

Table 88: Back-step Regression to Determine the Degree of the AR Process

<table>
<tr><th colspan="4">Table 88: Panel A</th></tr>
<tr><th colspan="4">Estimates of autocorrelations</th></tr>
<tr><th>Lag</th><th>Covariance</th><th>Correlation</th><th>−1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1</th></tr>
<tr><td>0</td><td>0.00642</td><td>1.000000 |</td><td>|********************|</td></tr>
<tr><td>1</td><td>0.00639</td><td>0.995425 |</td><td>|********************|</td></tr>
<tr><td>2</td><td>0.00636</td><td>0.990998 |</td><td>|********************|</td></tr>
<tr><td>3</td><td>0.00633</td><td>0.986521 |</td><td>|********************|</td></tr>
<tr><td>4</td><td>0.00630</td><td>0.982044 |</td><td>|********************|</td></tr>
<tr><td>5</td><td>0.00627</td><td>0.977567 |</td><td>|********************|</td></tr>
</table>

<table>
<tr><th colspan="4">Table 88: Panel B</th></tr>
<tr><th colspan="4">Backward elimination of autoregressive terms</th></tr>
<tr><th>Lag</th><th>Estimate</th><th>t-value</th><th>Pr > |t|</th></tr>
<tr><td>4</td><td>0.000159</td><td>0.02</td><td>0.9826</td></tr>
<tr><td>5</td><td>0.002392</td><td>0.64</td><td>0.5214</td></tr>
<tr><td>3</td><td>0.007417</td><td>1.42</td><td>0.1558</td></tr>
</table>

<table>
<tr><th colspan="4">Table 88: Panel C</th></tr>
<tr><th colspan="4">Estimates of autoregressive parameters</th></tr>
<tr><th>Lag</th><th>Coefficient</th><th>Standard error</th><th>t-value</th></tr>
<tr><td>1</td><td>−0.981511*</td><td>0.005226</td><td>−187.83</td></tr>
<tr><td>2</td><td>−0.013977*</td><td>0.005226</td><td>−2.67</td></tr>
</table>

Table 89: FGLS to Estimate the Regression without an Intercept

Table 89: Panel A			
Dependent variable: *ABS_ DISCACCR*			
Ordinary least squares estimates			
SSE	278.519398	**DFE**	36,617
MSE	0.00761	**Root MSE**	0.08721
SBC	–74,694.412	**AIC**	–74,736.954
MAE	0.05995382	**AICC**	–74,736.953
MAPE	210.009028	**Regress R-Square**	**0.5636**
Durbin-Watson	0.0081	**Total R-Square**	0.5636
NOTE: No intercept term is used. R-squares are redefined			

Table 89: Panel B						
Variable	**DF**	**Estimate**	**Standard error**	***t*-value**	**Approx Pr > |*t*|**	**Variable label**
ROA	1	–0.2799	0.002610	–107.27	<.0001	Return on assets
Size	1	0.0127	0.000107	118.99	<.0001	Size
BMR1	1	0.000182	0.000301	0.60	0.5458	Book-to-market ratio
LEV3	1	–0.002598	0.000279	–9.31	<.0001	Leverage
DTIMERS	**1**	**0.0430**	**0.001036**	**41.44**	**<.0001**	**Firms that time the market**

Table 90: AR (3) and GARCH (6) Are Used to Estimate the Regression without an Intercept

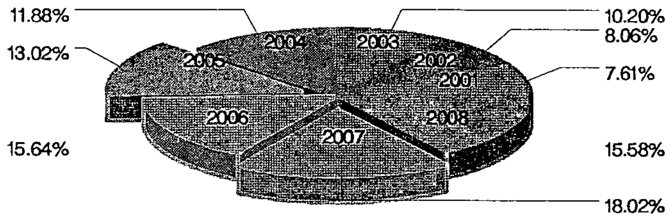
Table 90: Panel A			
		Estimates of autoregressive parameters	
Lag	**Coefficient**	**Standard error**	***t*-value**
1	−0.993369	0.005226	−190.08
2	−0.006092	0.007366	−0.83
3	0.003478	0.005226	0.67

Table 90: Panel B			
		GARCH estimates	
SSE	2.44314337	**Observations**	36,619
MSE	0.0000667	**Uncond. var.**	0
Log likelihood	152,435.119	**Total R-Square**	0.9962
SBC	−304,733.63	**AIC**	−304,844.24
MAE	0.06643957	**AICC**	−304,844.23
MAPE	129.946464	**Normality test**	2,591,810,040
		Pr > Chi-Sq	<.0001
NOTE: No intercept term is used. R-squares are redefined			

Table 90: AR (3) and GARCH (6) Are Used to Estimate the Regression without an Intercept (cont.)

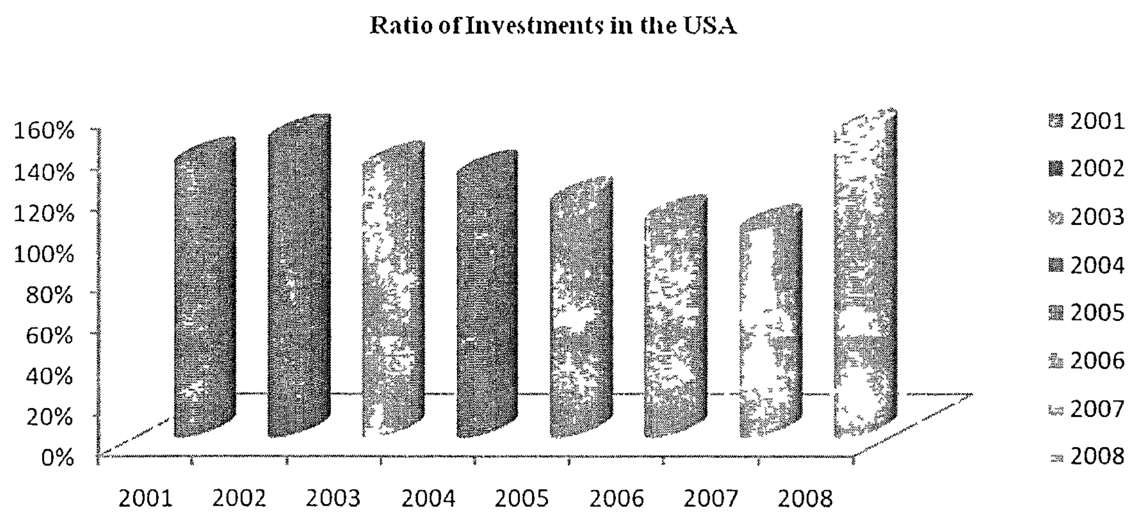
Table 90: Panel C						
Variable	**DF**	**Estimate**	**Standard error**	***t*-value**	**Approx Pr > |*t*|**	**Variable label**
ROA	1	–0.1576	0.0000857	–1,840.2	<.0001	Return on assets
Size	1	0.005704	6.0004E-6	950.64	<.0001	Size
BMR	1	–0.000597	0.0000211	–28.26	<.0001	Book-to-market ratio
LEV	1	0.004053	8.4586E-6	479.20	<.0001	Leverage
DTIMERS	**1**	**0.0121**	**0.0000393**	**308.61**	**<.0001**	**Firms that time the market**
AR1	1	–0.9829	0.003901	–252.00	<.0001	
AR2	1	0.002677	0.007850	0.34	0.7330	
AR3	1	0.0127	0.006835	1.86	0.0636	
ARCH0	1	2.5501E-6	2.3781E-9	1,072.32	<.0001	
ARCH1	1	0.2862	0.000379	755.32	<.0001	
ARCH2	1	0.0367	0.000849	43.21	<.0001	
ARCH3	1	0.0491	0.0148	3.32	0.0009	
ARCH4	1	1.2165	0.0167	72.65	<.0001	
ARCH5	1	7.107E-11	0.000285	0.00	1.0000	
ARCH6	1	2.999E-23	2.6562E-6	0.00	1.0000	

Figure 1: Total Portfolio Assets Investment in the USA, 2001–2008



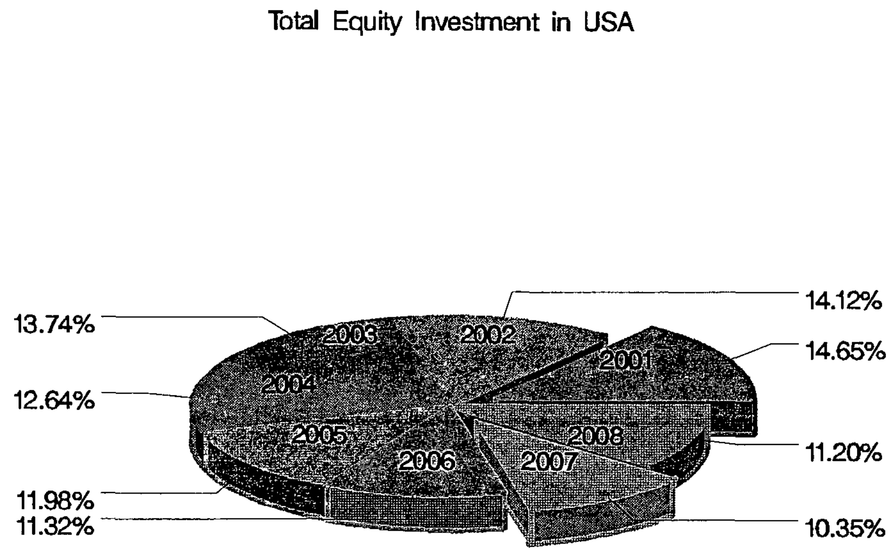
Source: United Nations web site.

Figure 2: Ratio of Total Asset Investments in the United States to Total Asset Investments from the United States



Source: United Nations.

Figure3: Total Equity Investments in the USA,2001–2008



Source: United Nations.

Figure 4: Histogram of Daily Returns, along with a Fitted Normal Curve and Kernel Density Function

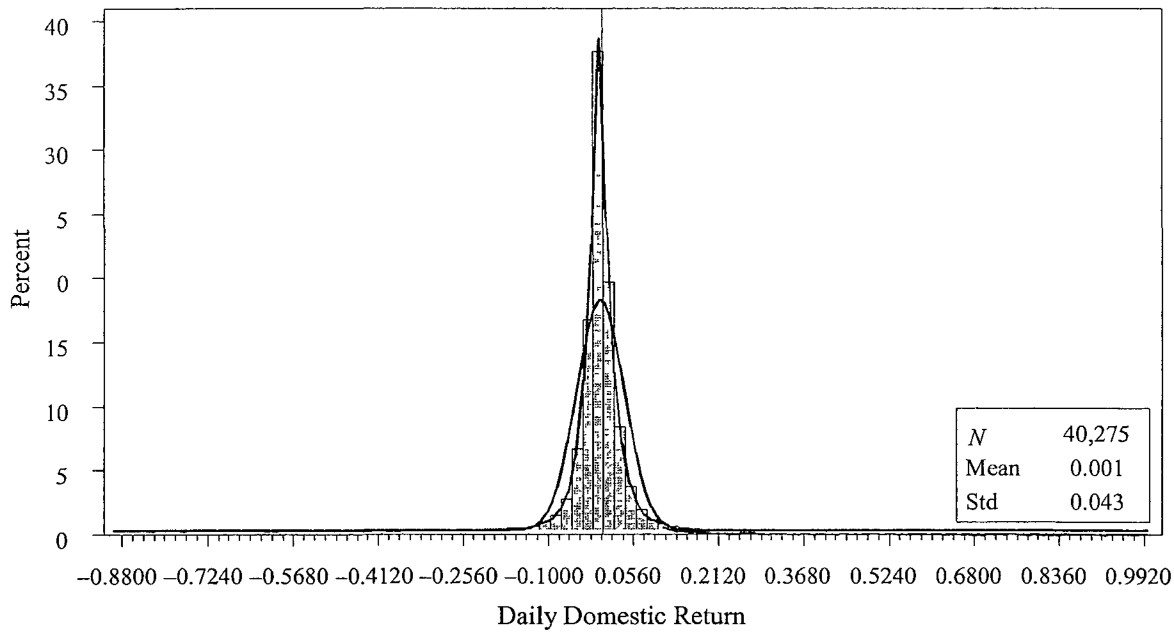


Figure 5: Probability Plot of Daily Returns

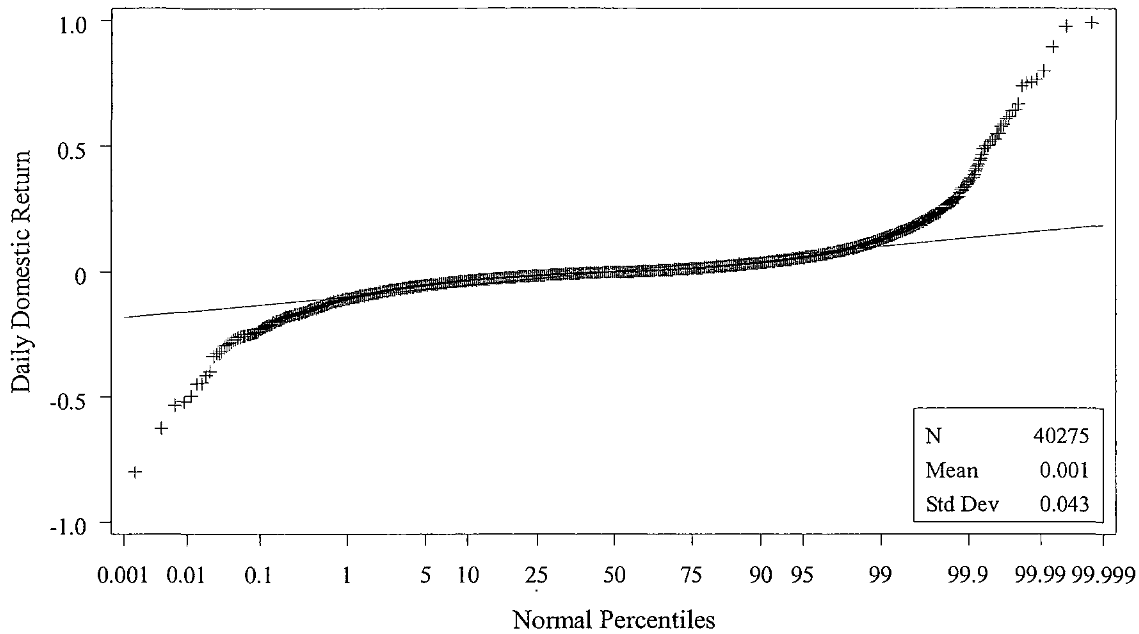


Figure 6: Points of Log Returns on the Superimposed Theoretical Normal Reference Line

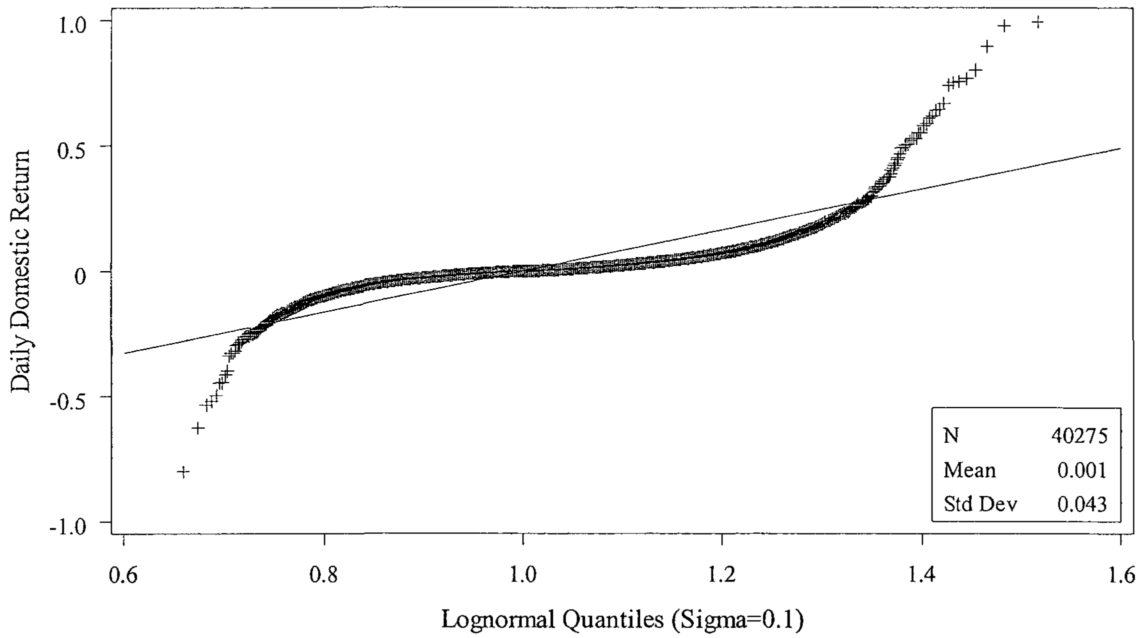


Figure 7: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = +LOBTM (0, +50)

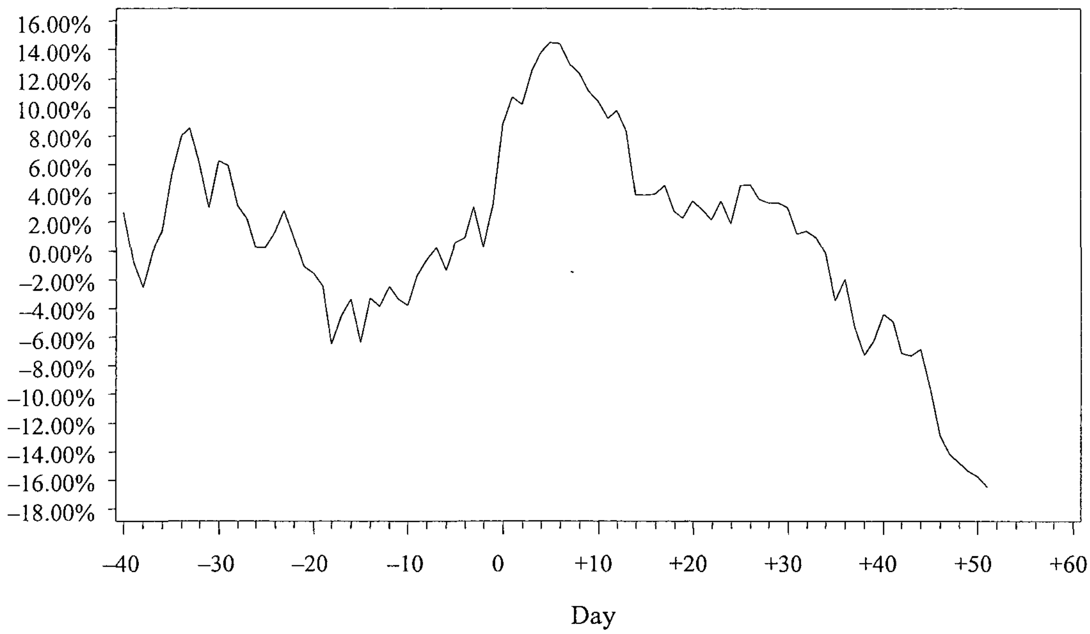


Figure 8: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce Different Results

Characteristics Index Distinction = –LOBTM (0, +50)

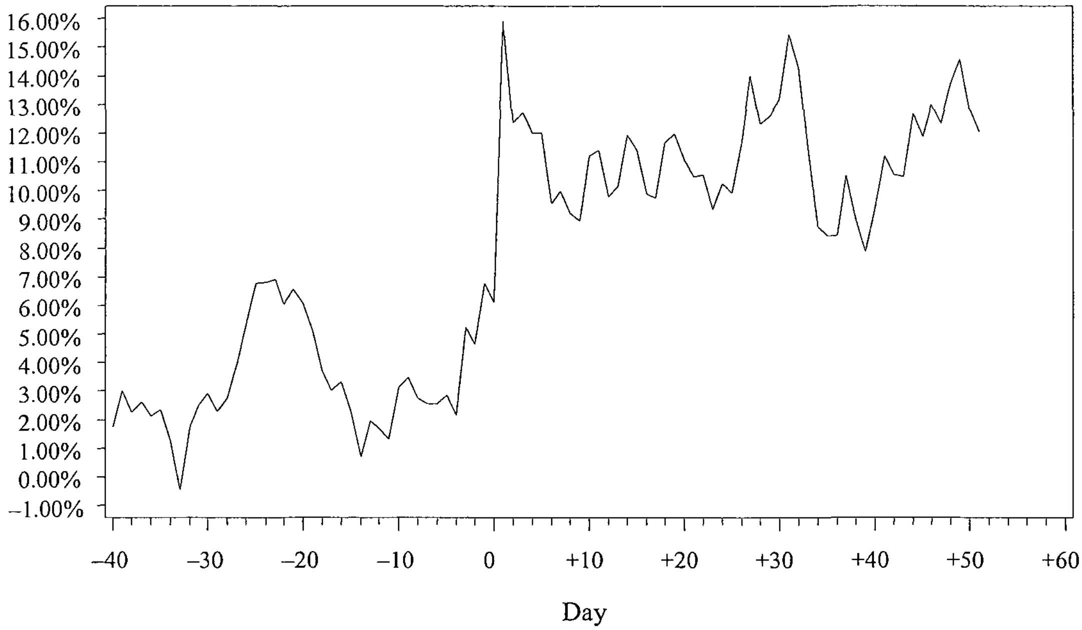


Figure 9: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = +HIBTM (0, +50)

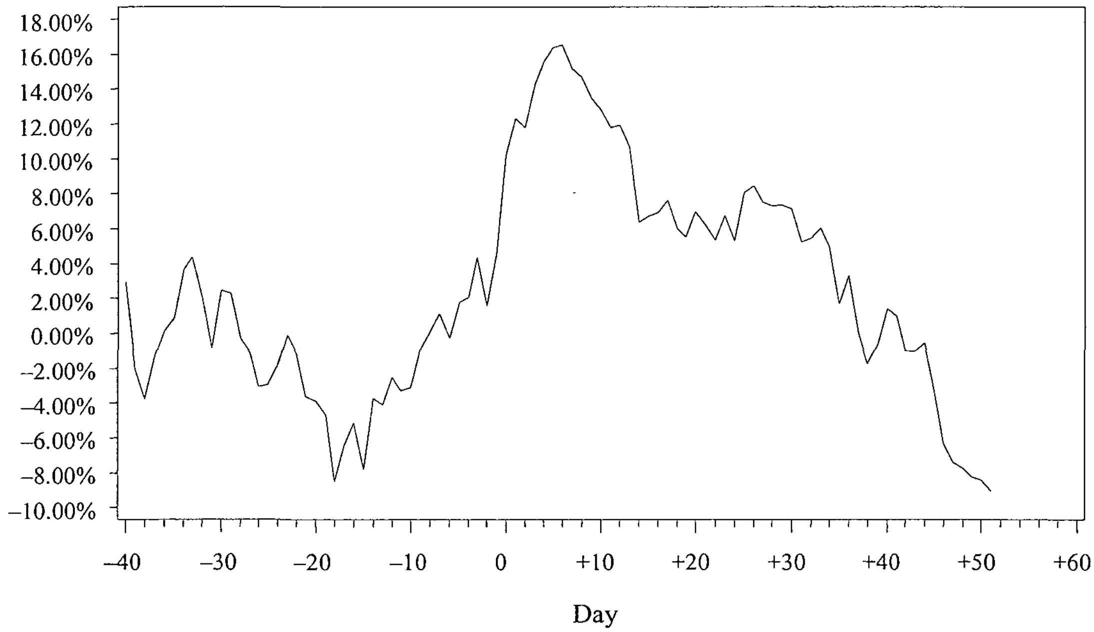


Figure 10: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce Different Results

Characteristics Index Distinction = –HIBTM (0, +50)

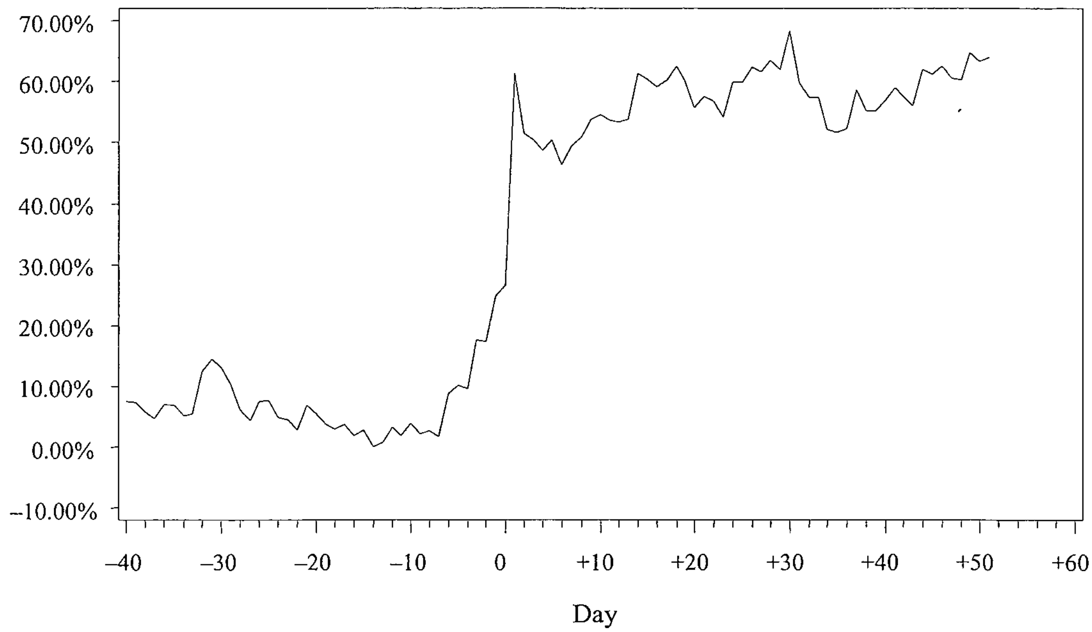


Figure 11: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = +SMALL (0, +50)

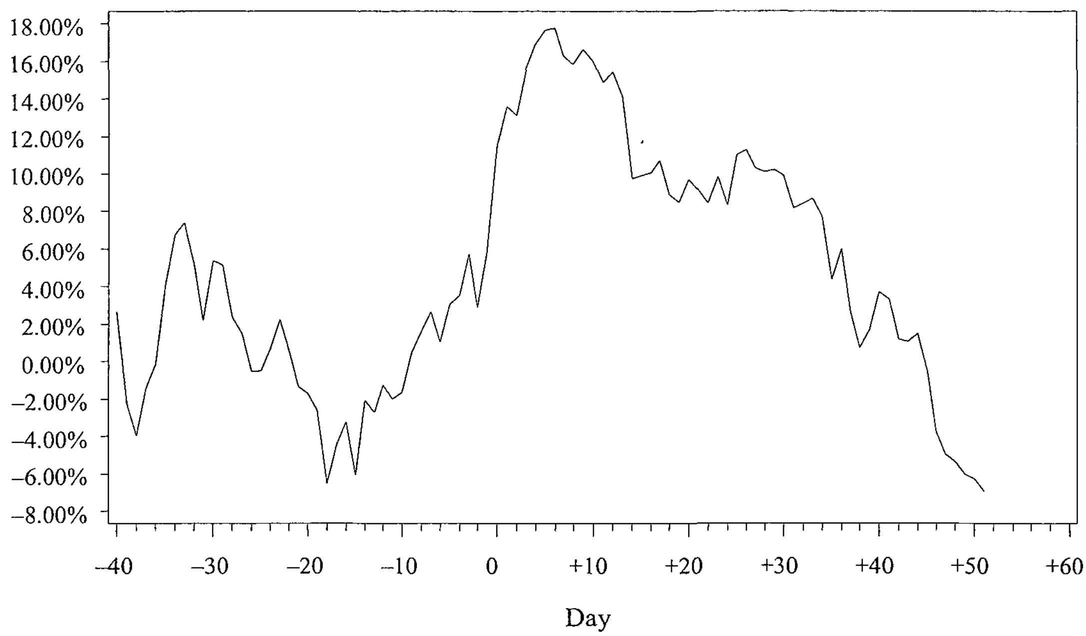


Figure 12: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce Different Results

Characteristics Index Distinction = –SMALL (0, +50)

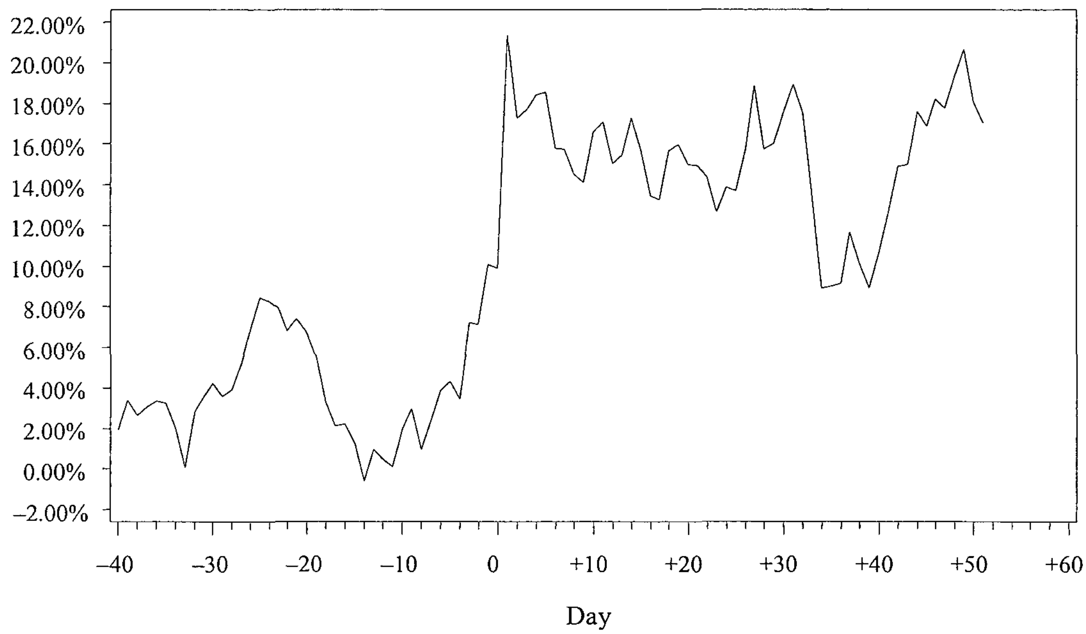


Figure 13: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = +BIG (0, +50)

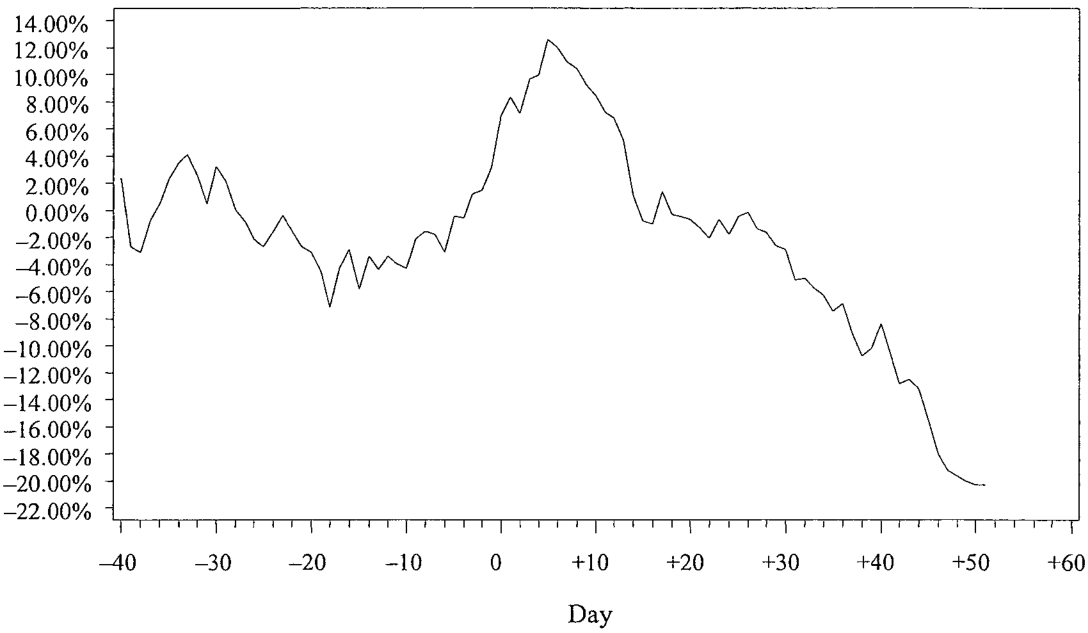


Figure 14: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = –BIG (0, +50)

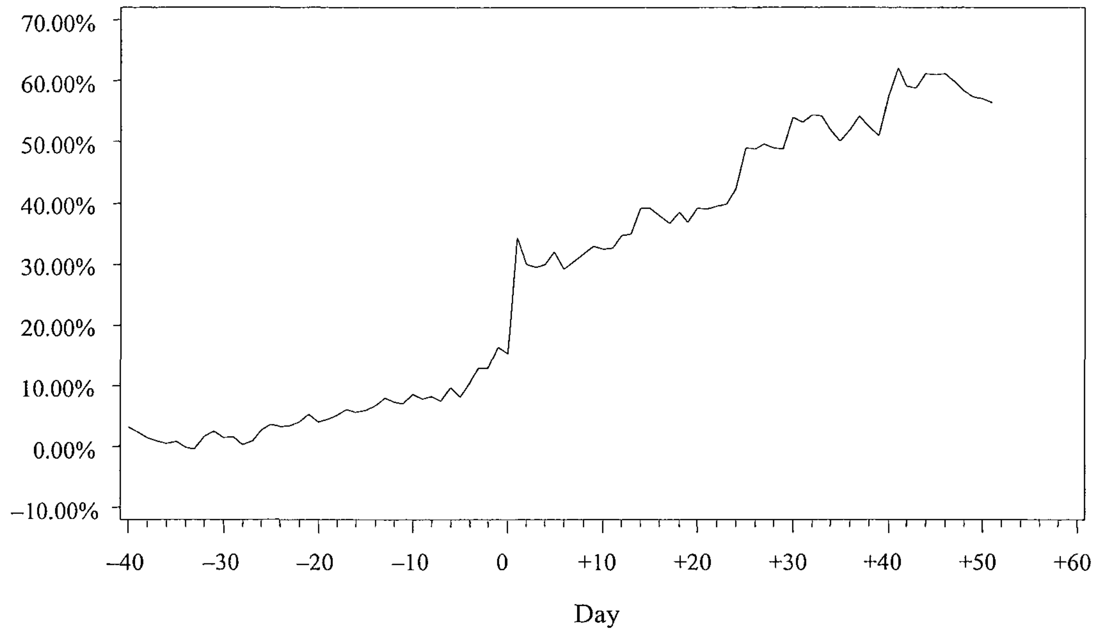


Figure 15: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Positive, and Companies Timing the Market Is Inconclusive. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = +SL (0, +50)

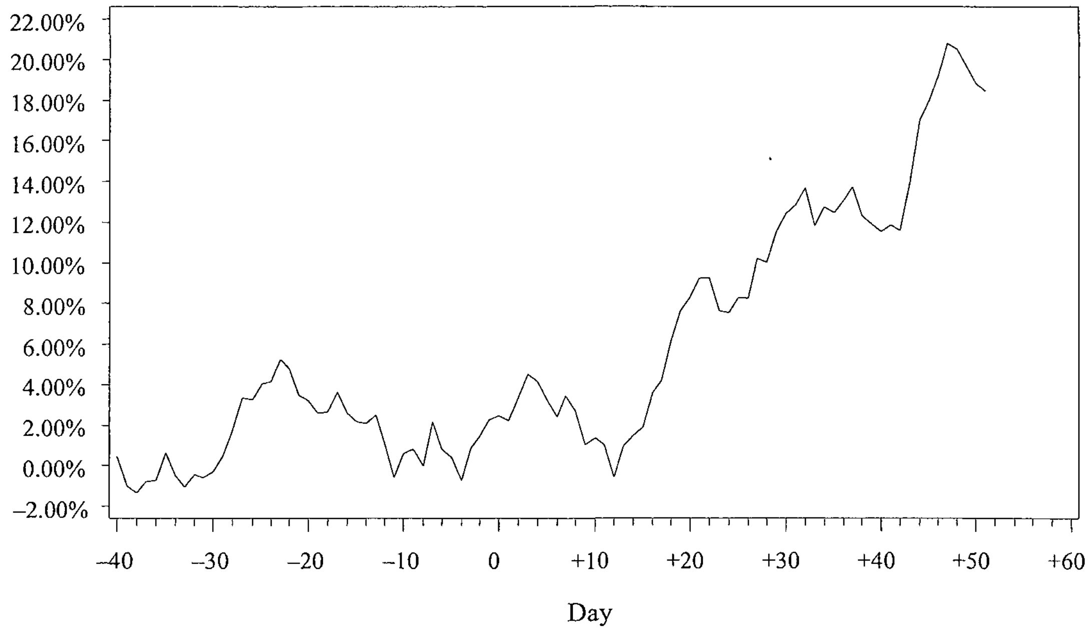


Figure 16: Post-listing Anomaly Exists. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = –SL (0, +50)

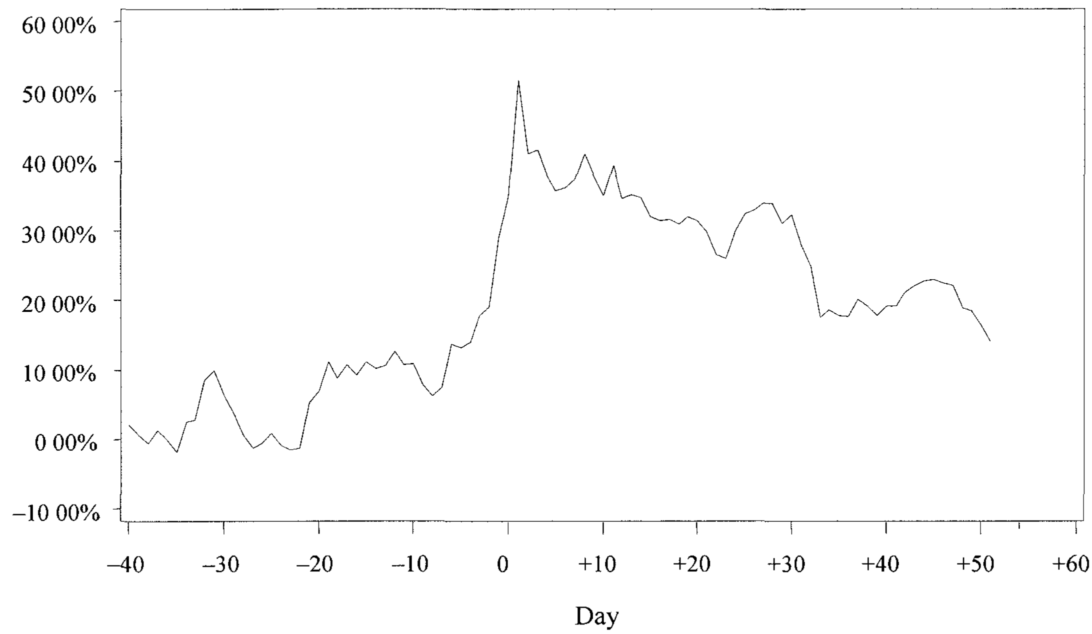


Figure 17: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Positive, and Companies Timing the Market Is Inconclusive. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = +HNLTR (0, +50)

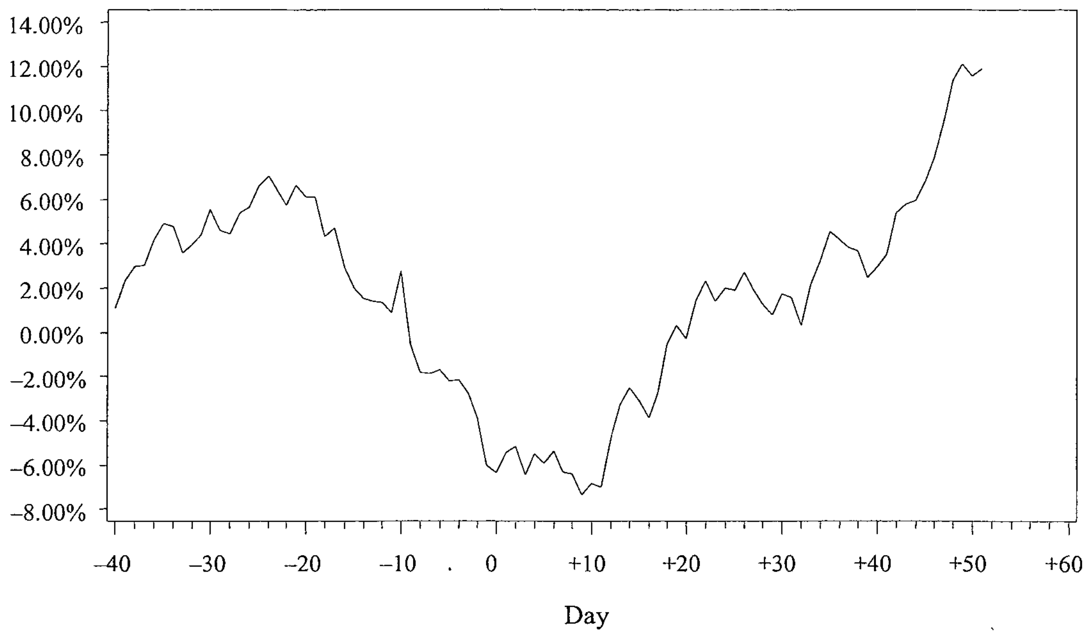


Figure 18: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = +HNSTR (0, +50)

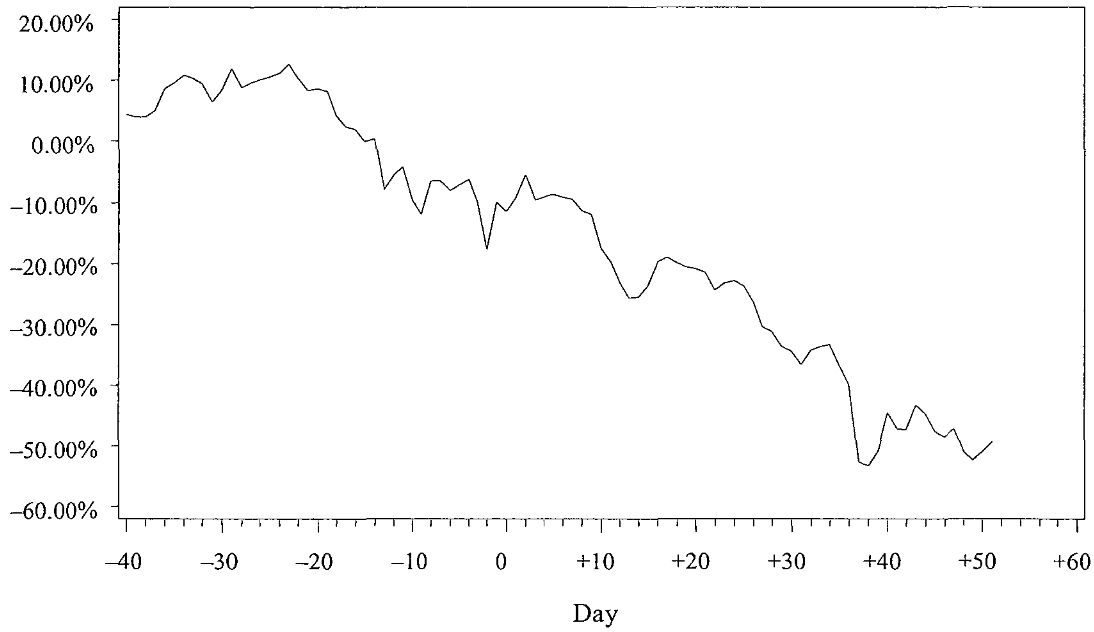


Figure 19: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = –HNLTR (0, +50)

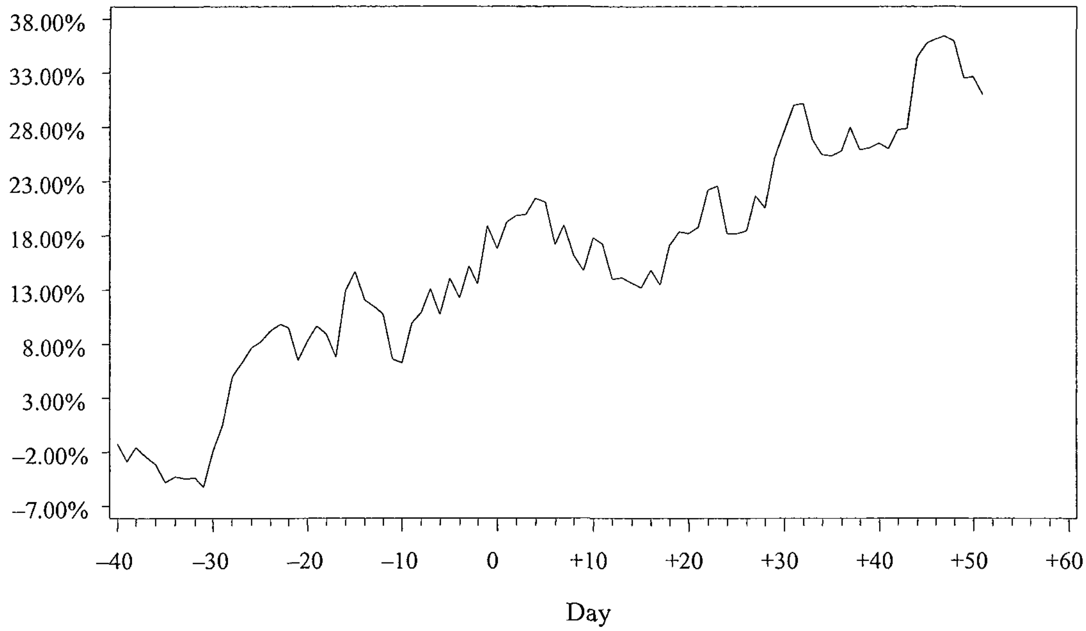


Figure 20: Post-listing Anomaly Exists. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = –HNSTR (0, +50)

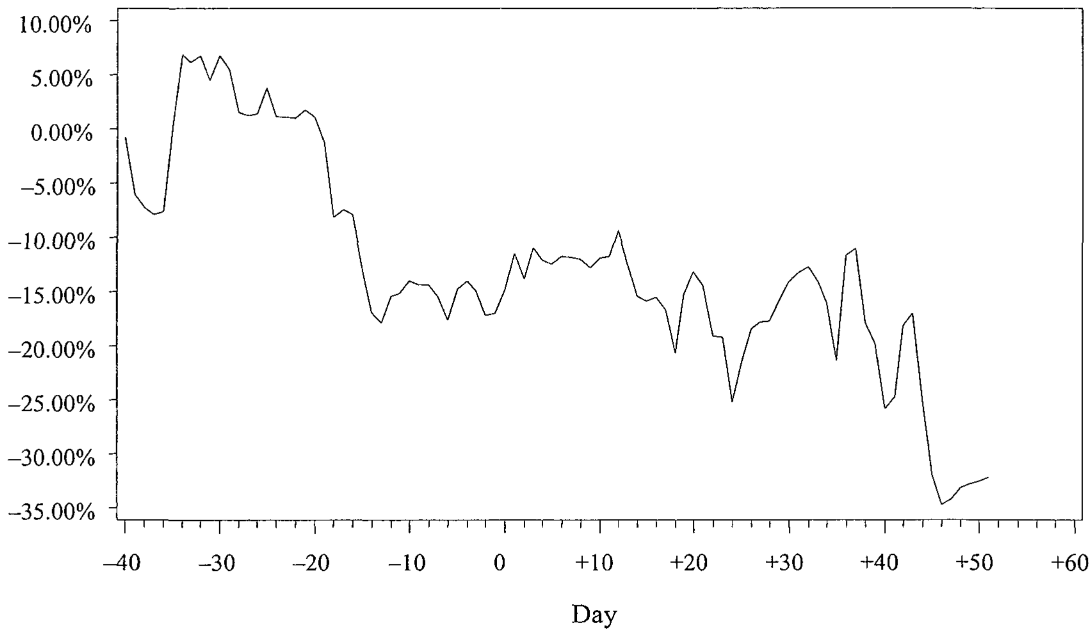


Figure 21: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Characteristics Index Distinction = +HPMOM (0, +50)

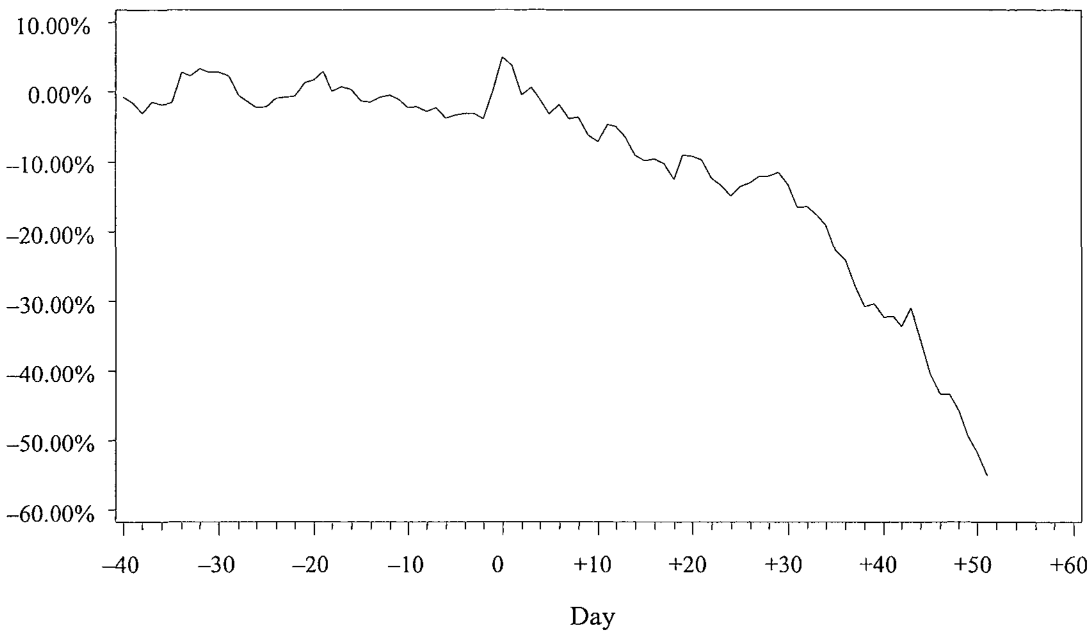


Figure 22: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Market Index Distinction = –HPMOM (0, +50)

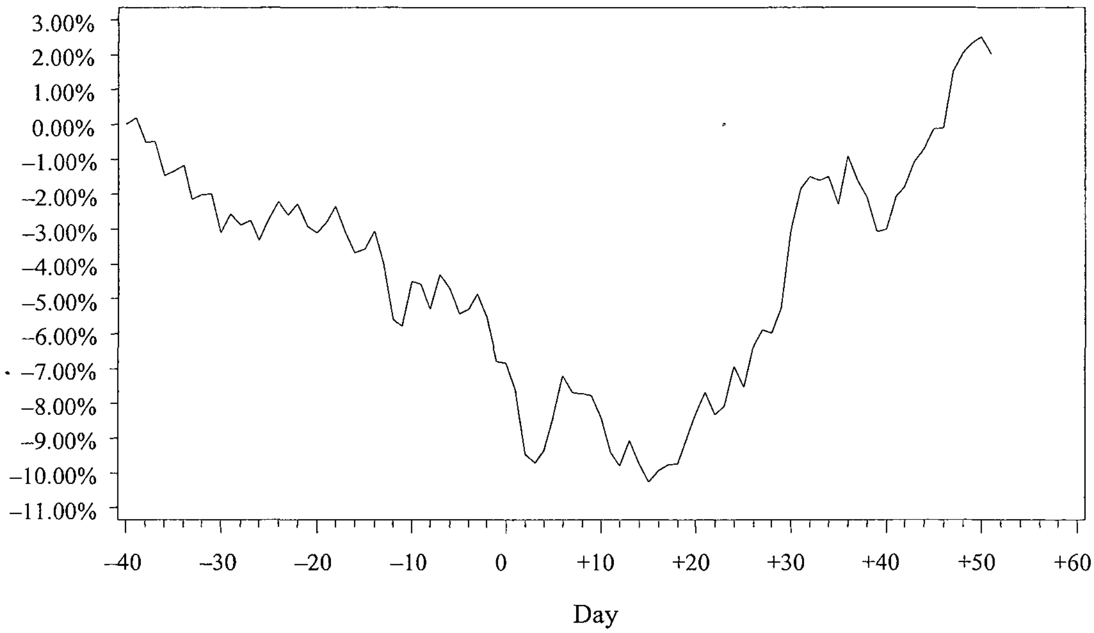


Figure 23: Post-listing Anomaly Exists. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Characteristic index distinction= -HPMOM (0, +50)

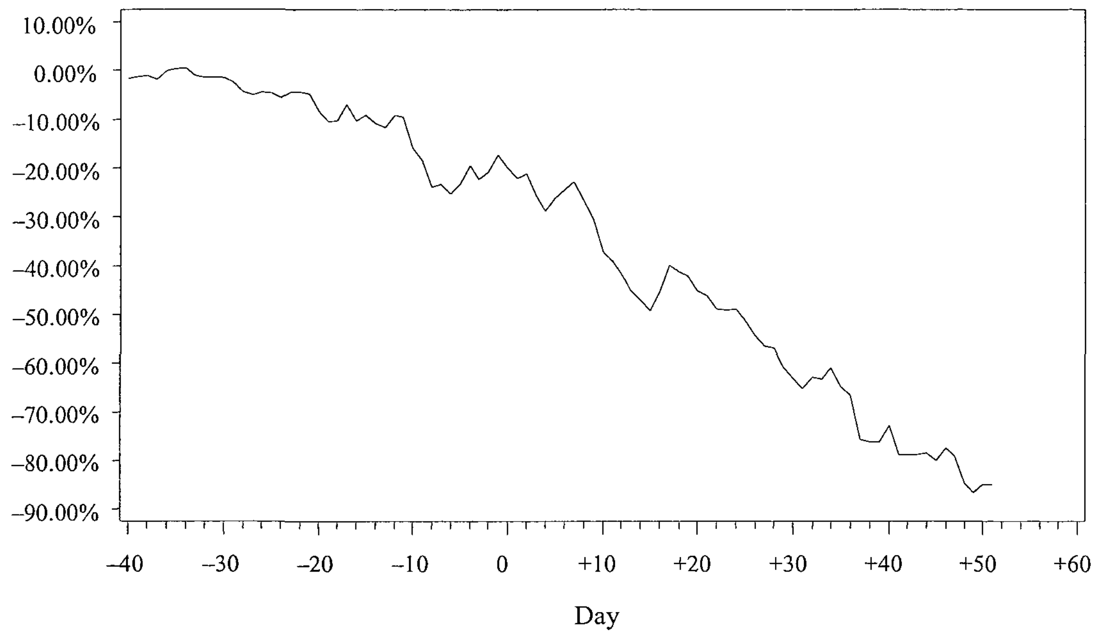


Figure 24: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Market index distinction = +SENT (0, +50)

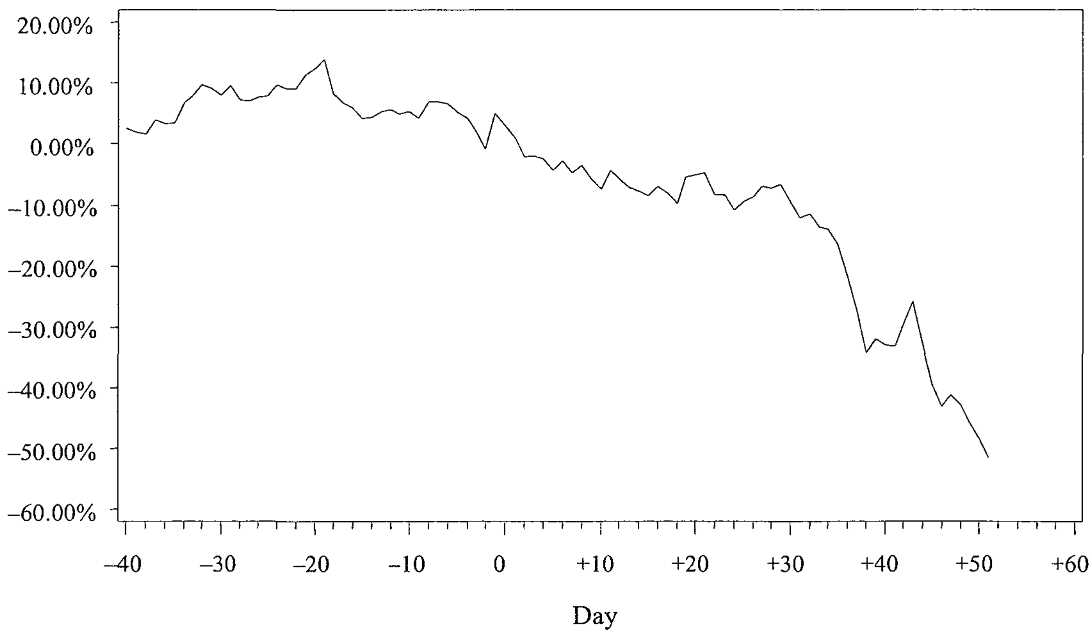


Figure 25: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Market index distinction = –SENT (0, +50)

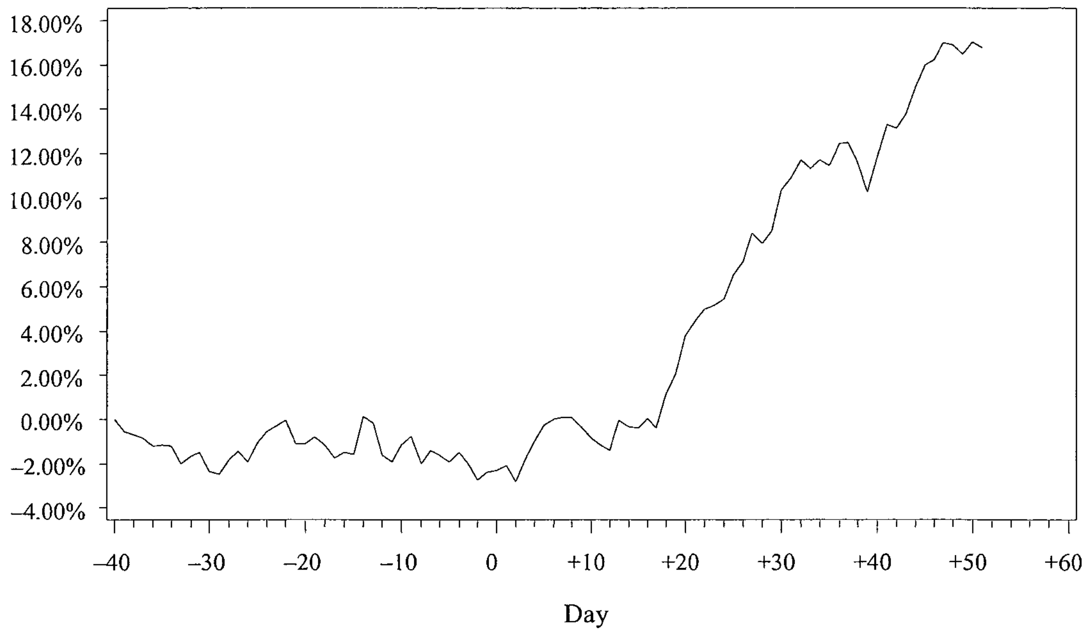


Figure 26: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Market index distinction = +MOM (0, +50)

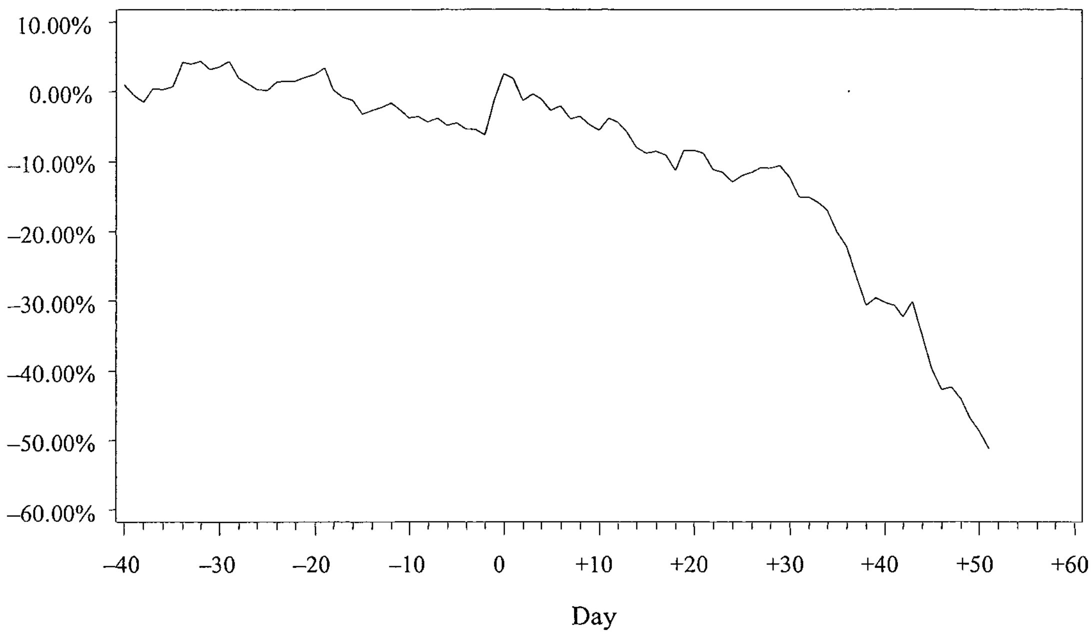


Figure 27: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Producethe Same Results

Market index distinction = –Mom (0, +50)

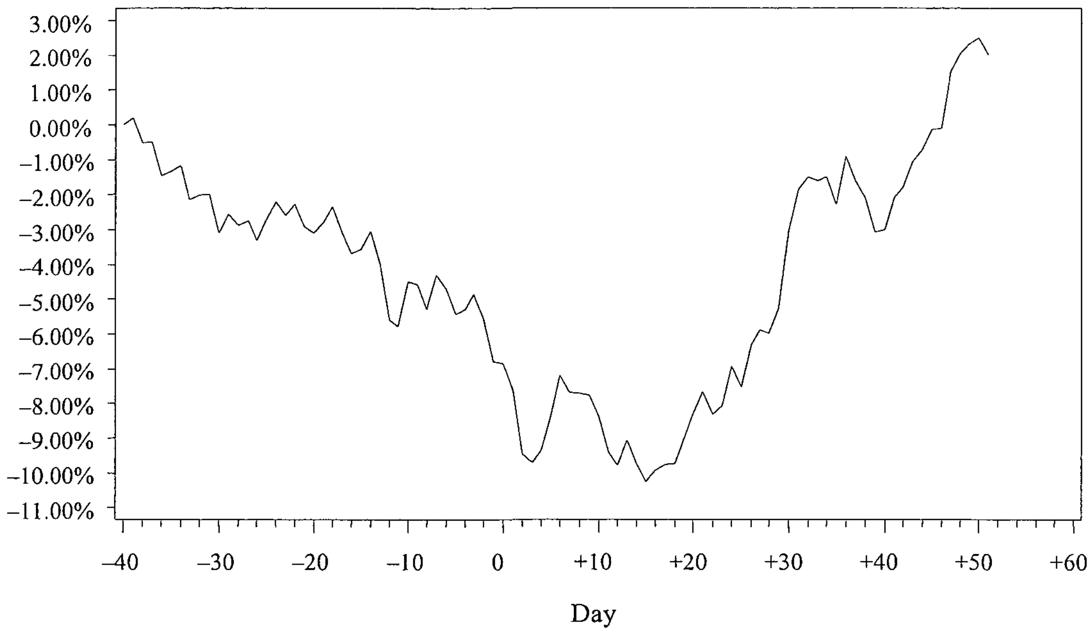


Figure 28: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Market index distinction = +LTR (0, +50)

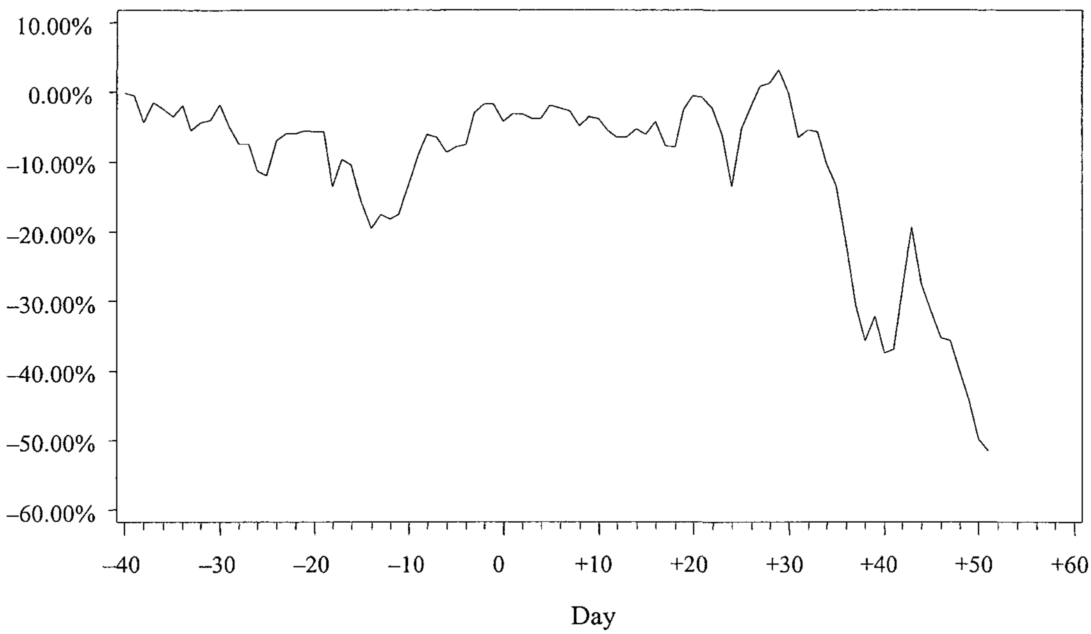


Figure 29: Post-listing Anomaly Exists. Host Market Condition Is a Positive, and Companies Time the Market. Different Estimation Procedures Produce the Same Results

Market index distinction = +STR (0, +50)

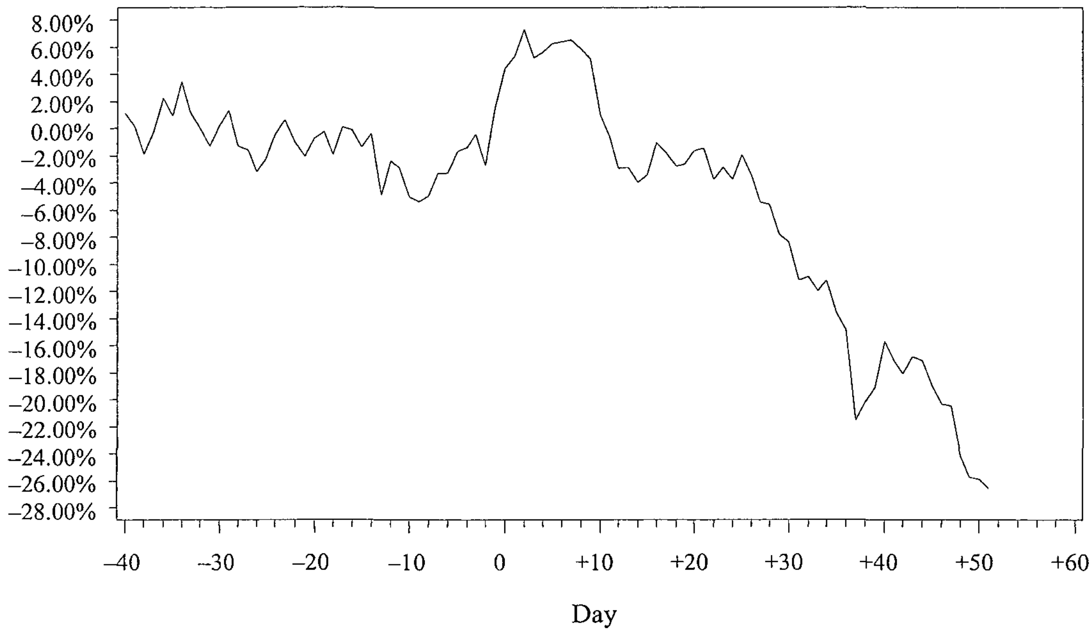


Figure 30: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Market index distinction = –LTR (0, +50)

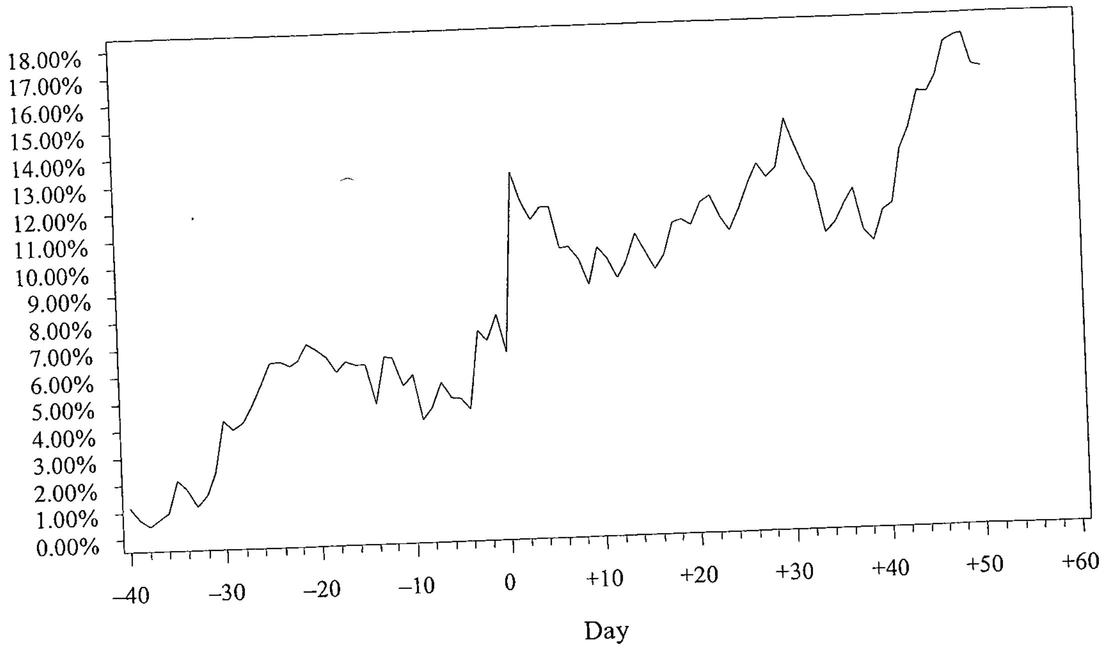


Figure 31: Post-listing Anomaly Does Not Exist. Host Market Condition Is a Negative, and Companies Do Not Time the Market. Different Estimation Procedures Produce the Same Results

Market index distinction = –STR (0, +50)

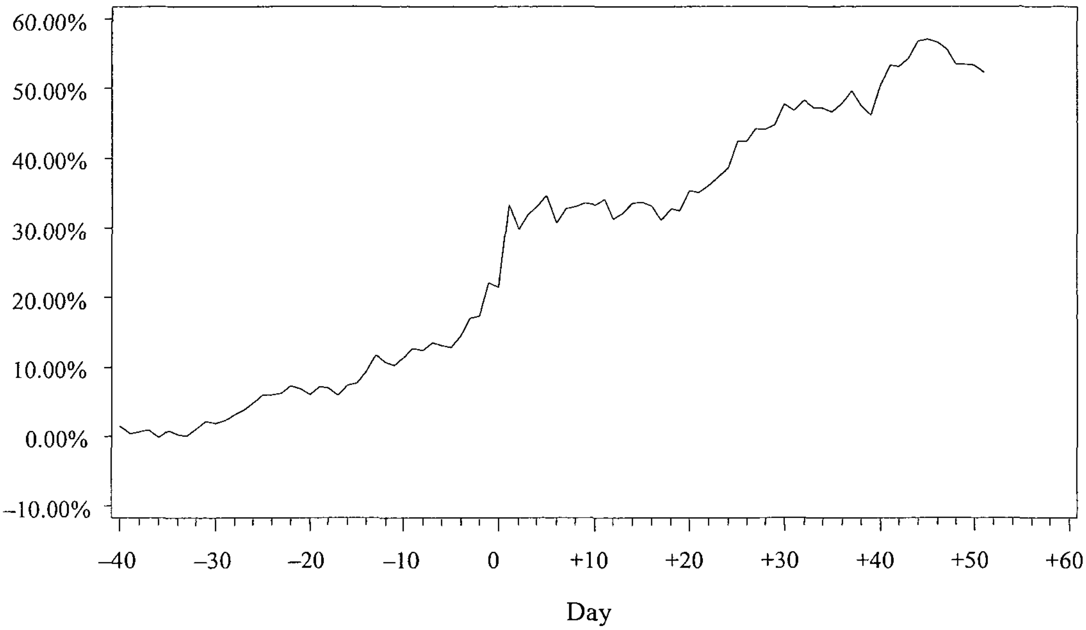
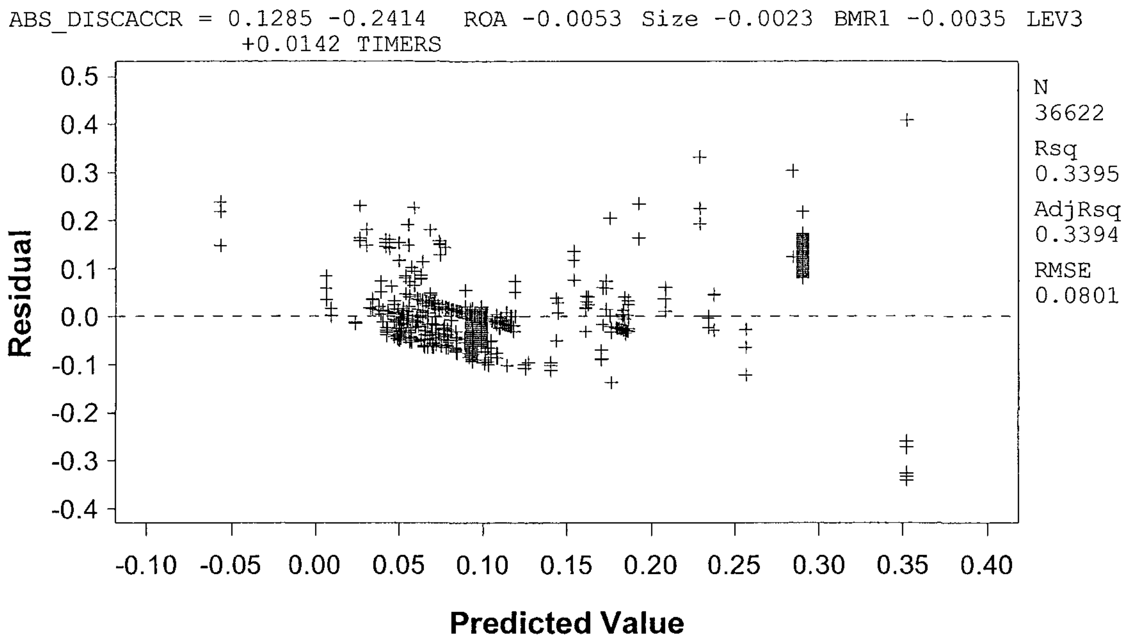


Figure 32: Fitted Values of the Dependent Variable against the Residual That Clearly Shows the Variance Is Not Homoscedastic



APPENDICES

APPENDIX A

A.1 Abnormal Return Estimation Using OLS[28]

Recent research model returns are drawn from either a fat-tailed distribution with finite higher moments, such as the τ distribution, or as a mixture of distributions. The result is a fat-tailed, unconditional distribution with a finite variance and higher moments. Since all moments are finite, the central limit theorem applies, and long-horizon returns will be closer to normal distribution than those of short-horizon returns.[29]

To discover the event impact, I need a measure of abnormal return, but first I define daily returns:

$$R_t = \frac{p_{t+1} - p_t}{p_t}$$

(A.1)

where R_t is the daily security i return at time t, p_{t+1} is the closing price of security i at time $t+1$, and p_t is the closing price of security $i$at time t. Abnormal return is the actual ex post return of the security over the event window minus the normal return of the firm over the event period. The normal return is defined as the return that would be expected if the event did not take place. For each firm i and event date τ I have

$$\epsilon_{it}^{*} = R_{it} - E\{R_{it}|H_t\}$$

(A.2)

where $\epsilon_{it}^{*}, R_{it}, E(R_{it})$ are the abnormal, actual, and normal returns, respectively, for time period $t. H_t$is the conditioning information for the normal performance model. I used the market model to model normal returns or expected returns where $H_t$is the market return. The market model assumes a stable linear relation between the market and the security return.

According to the market model, asset returns are jointly multivariate normal, independently and identically distributed through time (IID). Let $R_t$be an (Nx1) vector of asset returns for calendar time period $t. R_t$is independently multivariate normally distributed with mean μ and covariance matrix Ω for all t. The distributional assumption is sufficient for the constant mean return model and the market model to be correctly specified and allows for developing exact finite-sample distributional results for the estimators and the statistics. I will use the market model to calculate the normal and abnormal returns. The model's linear specification follows from the assumed joint normality of asset returns, thus for any security i, I have:

$$R_{it} = \alpha_{it} + \beta_{it} R_{mt} + \epsilon_{it}$$

(A.3)

[28] Event Study Analysis: CLM Chapter 4. (n.d.). Retrieved from\
http://home.business.utah.edu/finmll/fin787/slides/eventstudiesclm.pdf

[29] Lo and MacKinlay, The econometrics of financial markets (1996).

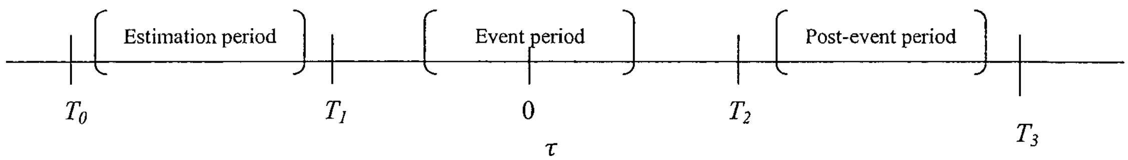
$E[\epsilon_{it}] = 0$

(A.4)

$VAR\ E[\epsilon_{it}] = \sigma_t^2$ (A.5)

where$R_{it}$and R_{mt} are the period t returns on security i and the market portfolio, respectively, and ϵ_{it} is the zero mean disturbance term. α_{it} ,β_{it},σ_t^2 are the parameters of the market model. I used the DJIA as the market portfolio (I used different indexes as well), because the firms in the sample were compared with firms included in the DJIA. The market model removes the portion of the return that is related tovariation in the market's returns; therefore, the variance of abnormal return is reduced, and this can lead to increased capacity to detect event effects.

Figure A.1: Time Line for Event Study



The returns in the event time are defined using τ. Defining $\tau = 0$ as the event date, $\tau = T_1 + 1$ to $\tau = T_2$ represents the event window, and $\tau = T_0 + 1$ to $\tau = T_1$ constitutes the estimation window. Let $\omega_1\, T_1 - T_0$ and $\omega_2 = T_2 - T_1$ be the length of the estimation window and event window, respectively. Post-event window will be from $\tau = T_2 + 1$ to $\tau = T_3$ and its length $\omega_3 = T_3 - T_2$.

This design assumes that abnormal return over the event window only occurs because of the event; as such, it is exogenous. In this design, the estimation window and the event window do not to overlap. The estimation window observations can be expressed as a regression system.

$R_i = H_i'\vartheta_i + \epsilon_i$

(A.6)

whereR_i=$[R_{iTn+1} \cdots\cdots\cdots R_{iT1}]'$ is a (ω_1 x1) vector of estimation window returns, H_i= $[\iota\ R_m]$ is an (ω_1x2) matrix with a vector of ones in the first column and the vector of market return observations R_m=$[R_{mTu+1} \ldots\ldots R_{mT1}]'$ in the second column, and ϑ_i =$[\alpha_i\beta_i]'$ is the (2x1) parameter vector. Hhas a subscript, because the estimation window may have timing that is specific to firm i.

Under general conditions, OLS is a consistent estimation procedure for the market-model parameters. Further, given that R_t is independently multivariate normally distributed with mean μ and covariance matrix Ω for all t, then OLS is efficient. The OLS estimators for the market-model parameters using an estimation window of ω_1 are

$\hat{\vartheta}_i = (H'_i H_i)^{-1} H'_i R_i$,

(A.7)

$\sigma_\epsilon^2 = \frac{1}{\omega_1 - 2}\hat{\epsilon}\hat{\epsilon}_i$,

(A.8)

$\hat{\epsilon}_i = R_i - H_i \hat{\vartheta}_i$,

(A.9)

$AR\left[\hat{\vartheta}_i\right] = (H'_i H_i)^{-1}\sigma_\epsilon^2$.

(A.10)

Given the market-model parameter estimates, I can measure and analyze abnormal returns. Let $\hat{\epsilon}_i^*$ be the (ω_2x1) sample vector of abnormal return for firm i for the event period $T_1 + 1$ toT_2 . Then using the market model to measure the normal return and the OLS estimators from equation (A.7), I have for the abnormal return vector:

$\hat{\epsilon}_i^* = R_i^* - \hat{\alpha}_i \iota - \hat{\beta}_i R_m^*$

(A.11)

$\hat{\epsilon}_i^* = R_i^* - H_i^* \hat{\vartheta}_i$

(A.12)

where$R_i^* = [R_{iT1} + 1 \cdots\cdots\cdots R_{iT2}]'$is a ($\omega_2$x1) vector of event window returns,$H_i^* = [\iota\ R_m^*]$ is an (ω_2x2) matrix with a vector of ones in the first column and the vector of market return observations $R_m^* = [R_{mT1} + 1 \ldots\ldots R_{mT2}]'$ in the second column, and $\hat{\vartheta}_i = \left[\hat{\alpha}_i \hat{\beta}_i\right]'$ is the (2x1) parameter vector estimates. Conditional on the market return over the event window, the abnormal returns will be jointly normally distributed with a zero conditional mean and conditional covariance matrix Ψ_i as shown below:

$E\{\hat{\epsilon}_i^* | H_i^*\} = E\left[R_i^* - H_i^* \hat{\vartheta}_i | H_i^*\right]$

(A.13)

$E\{\hat{\epsilon}_i^* | H_i^*\} = E\left[R_i^* - H_i^* \hat{\vartheta}_i) - H_i^*(\hat{\vartheta}_i - \vartheta_i) | H_i^*\right]$

(A.14)

$\mathrm{E}\{\hat{\epsilon}_i^* | H_i^*\} = 0$

(A.15)

$\Psi_i = E\{\hat{\epsilon}_i^* \hat{\epsilon}_i^{*'} | H_i^*\}$

(A.16)

$\Psi_i = E\{ [\hat{\epsilon}_i^* - H_i^*(\hat{\vartheta}_i - \vartheta_i)]\, [\hat{\epsilon}_i^* - H_i^*(\hat{\vartheta}_i - \vartheta_i)]' \, | H_i^* \}$

(A.17)

$\Psi_i = E[\epsilon_i^* \epsilon_i^{*'} - \epsilon_i^*(\hat{\vartheta}_i - \vartheta_i)' \acute{H}_i^* - H_i^*(\hat{\vartheta}_i - \vartheta_i)\epsilon_i^{*'} + H_i^*(\hat{\vartheta}_i - \vartheta_i)(\hat{\vartheta}_i - \vartheta_i)' H_i^{*'} | H_i^*]$

(A.18)

$\Psi_i = I\sigma_{\epsilon\iota}^2 + H_i^*(H'_i H_i)^{-1} H_i^{*'} \sigma_\iota^2$

(A.19)

From equation (A.15), the abnormal return vector has an expectation of zero, which is unbiased. The covariance matrix of the abnormal return vector in equation (A.19) has two parts. The first term is variance because of the future disturbances, and the second term is the additional variances due to the sampling error in $\hat{\vartheta}_i$. As the length of the estimation window $\omega_1$grows large, the second term will approach zero, as the sampling error of the parameters vanishes, and the abnormal returns over time will become independent asymptotically. Under H_0, for the vector of event window sample abnormal returns, I have $\hat{\epsilon}_i^* \sim N\ (0, \Psi_i\ )$, which gives the distribution for any single abnormal return observation.

A.2 Cumulative Abnormal Return Estimation and Testing (CAR)[30]

I considered aggregation over time for an individual security and then considered aggregation across securities and over time to accommodate multiple sampling intervals within the event window. First, the aggregation over time, using the time line shown in figure D.1: define $CAR\ (\tau_1, \tau_2)$ as the cumulative abnormal return for security i from τ_1 to τ_2 where $T_1 < \tau_1 \leq \tau_2 \leq T_2$. Let γ be an $(\omega_2 x1)$ vector with ones in positions $\tau_1 - T_1$ to $\tau_2 - T_1$ and zeroes across elsewhere. Then

$$\widehat{CAR}_i\ (\tau_1, \tau_2)\ \equiv \gamma\ '\hat{\epsilon}_i^*,$$

(A.20)

$$VAR[\widehat{CAR}_i\ (\tau_1, \tau_2)] = \sigma_i^2(\tau_1, \tau_2) = \gamma\ '\Psi_i\,\gamma.$$

(A.21)

It follows from $\hat{\epsilon}_i^* \sim N\ (0, \Psi_i\ )$ that under H_0: $\widehat{CAR}_i\ (\tau_1, \tau_2) \sim N[0, \sigma_i^2(\tau_1, \tau_2)]$, then a test of H_0 for security i from equation (A.21) using the standardized cumulative abnormal return, where

$$\widehat{SCAR}_i\ (\tau_1, \tau_2) = \frac{\widehat{CAR}_i\ (\tau_1, \tau_2)}{\sigma_i^2\ (\tau_1, \tau_2)}\ ,$$

(A.22)

and $\hat{\sigma}_i^2(\tau_1, \tau_2)$ is calculated with $\hat{\sigma}_i^2$ from

$$\sigma_\epsilon^2 = \frac{1}{\omega_1 - 2}\widehat{\epsilon\ '_i}\hat{\epsilon}_i.$$

(A.23)

Under the null hypothesis, the distribution of $\widehat{SCAR}_i\ (\tau_1, \tau_2)$ is sudent t with $\omega_2 - 2$ degrees of freedom. From the properties of the student t distribution, the expectation of $\widehat{SCAR}_i\ (\tau_1, \tau_2)$ is 0, and the variance is $[\ \frac{\omega_1 - 2}{\omega_1 - 4}]$. For a large estimation window (for example, ω_1>30), the distribution of $\widehat{SCAR}_i\ (\tau_1, \tau_2)$ will be well approximately by the standard normal.

To aggregate across securities and over time, there must not be any correlation across the abnormal returns of different securities, which will be the case in the absence of clustering. The maintained distributional assumptions imply that the abnormal returns and the cumulative abnormal returns will be independent across securities. The individual securities abnormal returns can be averaged using $\hat{\epsilon}_i^*$ from equation (D.12). Given a sample of N events, defining

$$\bar{\epsilon}^* = \frac{1}{N}\sum_{i=1}^{N}\hat{\epsilon}_i^*,$$

(A.24)

[30] Markets. Campbell. .Lo. (n.d.). Retrieved from http://www.scribd.com/doc/40811763/Markets-Campbell-Lo

$VAR[\bar{\epsilon}^*] = \Psi = \frac{1}{N^2}\sum_{i=1}^{N}\Psi_i.$

(A.25)

That average abnormal returns vector can be aggregated over time, as such, define $\overline{CAR}(\tau_1, \tau_2)$ as the CAAR from τ_1 to $\tau_2$where $T_1 < \tau_1 \leq \tau_2 \leq T_2$. Let γ be an (ω_2x1) vector with ones in positions $\tau_1 - T_1$ to $\tau_2 - T_1$ and zeroes elsewhere. CAAR:

$\overline{CAR}(\tau_1, \tau_2) \equiv \acute{\gamma}\bar{\epsilon}^*,$

(A.26)

$VAR[\overline{CAR}(\tau_1, \tau_2)] = \bar{\sigma}^2(\tau_1, \tau_2) = \gamma' \Psi\gamma.$

(A.27)

Equivalently to obtain $\overline{CAR}(\tau_1, \tau_2)$, the aggregation will use the sample cumulative abnormal return for each security$i$. For N events:

$\overline{CAR}(\tau_1, \tau_2) = \frac{1}{N}\sum_{i=1}^{N}\widehat{CAR}_i(\tau_1, \tau_2),$

(A.28)

$VAR[\overline{CAR}(\tau_1, \tau_2)] = \bar{\sigma}^2(\tau_1, \tau_2) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_i^2(\tau_1, \tau_2).$ (A.29)

In equations (D.25), (D.27), and (D.29), the assumption was that the event windows N securities do not overlap to set the covariance terms to zero. Inferences about the cumulative abnormal returns can be drawn using $\overline{CAR}(\tau_1, \tau_2) \sim N(0, \bar{\sigma}^2(\tau_1, \tau_2))$, since under the null hypothesis the expectation of the abnormal return is zero. In practice, since $\bar{\sigma}^2(\tau_1, \tau_2)$ is unknown, then:

$\hat{\bar{\Sigma}}^2(\tau_1, \tau_2) = \frac{1}{N^2}\sum_{i=1}^{N}\hat{\sigma}_i^2(\tau_1, \tau_2),$

(A.30)

is a consistent estimator, and the null hypothesis can be tested using

$\Pi_1 = \frac{\overline{CAR}(\tau_1, \tau_2)}{\sqrt{[\hat{\bar{\sigma}}^2(\tau_1, \tau_2)]}} \stackrel{a}{\sim} N(0,1).$ (A.31)

A second model of aggregation is to give equal weighting to the individual $SCAR_{i's}$ defining $\overline{SCAR}(\tau_1, \tau_2)$ as the average over N securities from event time τ_1 to τ_2:

$\overline{SCAR}(\tau_1, \tau_2) = \frac{1}{N}\sum_{i=1}^{N}\widehat{SCAR}_i(\tau_1, \tau_2).$

(A.32)

Assuming that the event windows of the N securities do not overlap in calendar time, under $H_0\overline{SCAR}(\tau_1, \tau_2)$ will be normally distributed in large samples with a mean of zero and variance of [$\frac{\omega_4 - 2}{N(\omega_4 - 4)}$], so the test for the null hypothesis will be using

$\Pi_2 = \left[\frac{\omega_4 - 2}{N(\omega_4 - 4)}\right]^{.5} \overline{SCAR}(\tau_1, \tau_2) \stackrel{a}{\sim} N(0,1).$

(A.33)

On the one hand, if the true abnormal return is constant across securities, then the better choice will give more weight to the securities with lower abnormal return variances, which is what Π_2 does. On the other hand, if the true abnormal return is larger for securities with higher variance, then the better choice will give equal weight to the realized cumulative abnormal return of each security, which is what Π_1 does. However, in most cases, the results are not likely to be sensitive to the choice of Π_1 versus Π_2, because the variance of the *CAR* is of similar magnitude across securities. I will use Π_2 to generate our *t*-test statistics.

A.3 Market-adjusted Return Model[31]

Market-adjusted returns are computed by subtracting the observed return on the market index from day $t.R_{mt}$, from the rate of return of the common stock of the j^{th} firm on day:

$$A_{jt} = R_{jt} - R_{mt}.$$

(A.34)

A.4 Comparison Period Mean-adjusted Returns[32]

Comparison period mean-adjusted returns are computed by subtracting the arithmetic mean return of the common stock of the j^{th} firm computed over the estimation period $\bar{R}_j$ from its return on day t:

$$A_{jt} = R_{jt} - \bar{R}_j.$$

(A.35)

A.5 Returns across Time and Securities[33]

Ibbotson, (1975) developed a model called Returns across time and securities model by (Unlike the conventional market model, the RATS regression is estimated for each period in event time. The estimate of the mean abnormal return is $\alpha_t = 0$. The sum of the mean abnormal returns is the mean cumulative abnormal return. To test the significance, the assumption is time-series independence, hence the denominator of the test statistic for a window is the square root of the sum of the squares of the test-statistic denominators for the individual days that make up the window of analysis.

[31] I will not report results for such a model, because it is statistically inferior to the market model and produces conflicting results.
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APPENDIX B[34]

B.1 Parametric Tests[35]

The parametric tests proposed in the literature rely on the important assumption that an individual firm's abnormal returns are normally distributed. The standard statistic is:

$$t = \frac{\overline{AR}_O}{S(\overline{AR}_O)},$$

(B.1)

where $\overline{AR}_o$ is defined as the abnormal return, and $S(\overline{AR}_o)$ is defined as an estimate of standard deviation of the average abnormal return $\sigma(\overline{AR}_o)$.

Then, considering cross–sectional independence, that is, that the residuals are not correlated across securities,

$$\sigma^2[\overline{AR}_o] = \sigma^2\left(\sum_{i=1}^{N} \frac{AR_{io}}{N}\right) = \left(\frac{1}{N^2}\right)\sum_{i=1}^{N} \sigma^2\,(AR_{io}).$$

(B.2)

The standard deviation of the average abnormal return for each security $\sigma(\overline{AR}_{io})$, is then estimated on the basis of the standard deviation of the time-series of abnormal returns of each firm during the estimation period (T weeks), as follows:

$$S(AR_i) = \sqrt{\frac{\left[\sum_{t=1}^{T}[AR_{it}] - \frac{\sum_t AR_{it}}{T}\right]^2}{T-d}}.$$

(B.3)

Under the null hypothesis of no abnormal return performance, the statistic above is distributed with student-*t* with *T–D* degrees of freedom.

Previous studies have shown that abnormal returns distributions show fat tails and are right-skewed. Parametric tests reject too often when testing for positive abnormal performance and too seldom when testing for negative abnormal performance. When the assumption of normality of abnormal returns is violated, parametric tests are not well-specified. Non-parametric tests are well-specified and more powerful at detecting a false null hypothesis of no abnormal returns.

B.2 Patell Test and Corrected *t*-Statistic

The literature also refers to the Patell test as a standardized abnormal return test or a test assuming cross-sectional independence. Many published studies use the Patell test (Linn and McConnell, 1983; Schipper and Smith, 1986; Haw, Pastena and Lilien, 1990).

Under the null hypothesis, each A_{jt} has mean zero and variance $\sigma^2_{A_{jt}}$. The maximum likelihood estimate of the variance is

[34] Event Study Tests A brief survey. (n.d.). Retrieved from http://www.fep.up.pt/investigacao/workingpapers/wp117.pdf

[35] The trading bell at the New York stock exchange. (n.d.). Retrieved from http://www.freepatentsonline.com/article/Review-Business-Research/178079357.html

$$S_{A_{jt}}^2 = S_{A_j}^2\left[1 + \frac{1}{M_j} + \frac{(R_{mt}-\overline{R_{mEst}})^2}{\sum_{K=E_1}^{E_2}(R_{mt}-\overline{R_{mEst}})^2}\right],$$

(B.4)

where

$$S_{A_j}^2 = \frac{\sum_{K=E_1}^{E_2} A_{jk}^2}{M_j-2}.$$

(B.5)

$R_{mt}$is the observed return on the market index on day t, $\overline{R_{mEst}}$ is the mean market return over the estimation period, and M_j is the number of non-missing trading day returns in the interval E_1 through E_2 used to estimate the parameters for firm j.

Define the standardized abnormal return as

$$SAR_{jt} = \frac{A_{jt}}{S_{A_{jt}}}.$$

(B.6)

Under the null hypothesis, each SAR_{jt} follows a Student's t distribution with $M_j - 2$ degrees of freedom. Summing the SAR_{jt} across the sample, we obtain

$$TSAR_t = \sum_{j=1}^{n} SAR_{jt}.$$

(B.7)

The expected value of $TSAR_t$ is zero. The variance of $TSAR_t$ is

$$Q_t = \sum_{j=1}^{n} \frac{M_j-2}{M_j-4}.$$

(B.8)

The test statistic for the null hypothesis that $CAAR_{T_1,T_2} = 0$ is

$$Z_{T_1,T_2} = \frac{1}{\sqrt{N}}\sum_{j=1}^{n} Z^j{}_{T_1,T_2},$$

(B.9)

$$Z^j{}_{T_1,T_2} = \frac{1}{\sqrt{Q^j{}_{T_1,T_2}}}\sum_{t=T_1}^{n} SAR_{jt},$$

(B.10)

$$Q^j{}_{T_1,T_2} = (T_2 - T_1 + 1)\frac{M_j-2}{M_j-4}.$$

(B.11)

Under cross-sectional independence of $Z^j{}_{T_1,T_2}$ and other conditions, Z_{T_1,T_2} follows the standard normal distribution under the null hypothesis.

If abnormal returns are serially uncorrelated, the variance CAR_j is the sum of the variances of daily abnormal returns:

$$S^2CAR_{T_{1j},T_{2j}} = S_{A_j}^2 \left[L_j + \frac{L_j}{M_j} + \frac{\sum_{t=T_{1j}}^{T_{2j}} (R_{mt} - \overline{R_{mEst}})^2}{\sum_{k=1}^{M_j} (R_{mt} - \overline{R_{mEst}})^2} \right].$$

(B.12)

Instead of using average standardized abnormal returns, I report precision-weighted CAAR. The precision-weighted average is constructed using the relative weights implied by the definition Z_{T_1,T_2}. Thus, the precision-weighted average will always have the same sign as the corresponding Z_{T_1,T_2}. The formula for precision-weighted average is

$$PWCAR_{T_1,T_2} = \sum_{j=1}^{n} \sum_{t=T_1}^{T_2} W_j \; A_{jt},$$

(B.13)

where

$$W_j = \frac{\left(\sum_{t=T_1}^{T_{2j}} S_{A_{jt}}^2\right)^{\frac{-1}{2}}}{\sum_{i=1}^{n} \left(\sum_{t=T_1}^{T_{2j}} S_{A_{jt}}^2\right)^{\frac{-1}{2}}}.$$

(B.14)

The precision-weighted AR, as a weighted average of the original CAR_s, preserves the portfolio interpretation that $CAAR$ offers but average $SCAR$ does not.

The Patell test statistics for abnormal returns cumulated over specific periods are not adjusted for serial dependence. Mikkelson and Partch (1988) perform such correction on collative returns. The serial dependence is not due to any presumed dependence in true market-model error terms, but occurs because all of the abnormal return estimators being cumulated are functions of the same estimators of the market-model parameters. The derivation of the corrected standard error used by Mikkelson and Partch (1988) requires that the abnormal return be interpreted as forecast error.

If abnormal returns are serially correlated, then following Mikkelson and Partch (1988), the corrected test statistic for the null hypothesis that $CAAR = 0$ is

$$Z_{CAAR} = N^{\frac{-1}{2}} \sum_{j=1}^{n} \frac{CAR_{T_{1j},T_{2j}}}{S_{CAR_{T_{1j},T_{2j}}}},$$

(B.15)

where

$$S^2CAR_{T_{1j},T_{2j}} = S_{A_j}^2 \left\{ L_j \left[1 + \frac{L_j}{M_j} + \frac{\sum_{t=T_{1j}}^{T_{2j}} (R_{mt} - \overline{R_{mEst}})^2}{\sum_{k=1}^{M_j} (R_{mt} - \overline{R_{mEst}})^2} \right] \right\}.$$

(B.16)

The corrected test accounts for the fact that within the window, the abnormal returns for each stock are serially correlated. The serial correlation occurs because all the abnormal returns are functions of the same market-model intercept and slope estimators.

B.3 Standardized Cross-Sectional Test

Boehmer et al., (1991)introduce the standardized cross-section test. The test is the same as the Patell test described above except that there is a final empirical cross-sectional variance adjustment in place of the analytical variance of the total standardized prediction error.

For day t in the event period, the test statistic is

$$Z_t = \frac{TSAR_t}{N^{\frac{1}{2}}(S_{SAR_t})},$$

(B.17)

where

$$S^2{}_{SAR_t} = \frac{1}{N-1}\sum_{i=1}^{n}\left(SAR_{it} - \frac{1}{N}\sum_{j=1}^{n} SAR_{it}\right)^2.$$

(B.18)

The test is extended to multi-period using the serial correlation described above. Define the standardized cumulative abnormal return for stock j as

$$SCAR_{T_{1j},T_{2j}} = \frac{CAR_{T_{1j},T_{2j}}}{S\,CAR_{T_{1j},T_{2j}}},$$

(B.19)

where $SCAR_{T_{1j},T_{2j}}$ is as defined in equation. Then, the standardized cross-sectional test statistic for the null hypothesis that $CAAR = 0$ is

$$Z_t = \frac{\sum_{i=1}^{n} SCAR_{T_{1j},T_{2j}}}{N^{\frac{1}{2}}(S_{SCAR_t})},$$

(B.20)

where

$$S^2{}_{SCAR_t} = \frac{1}{N-1}\sum_{i=1}^{n}\left(SCAR_{T_{1i},T_{2i}} - \frac{1}{N}\sum_{j=1}^{n} SCAR_{T_{1j},T_{2j}}\right)^2.$$

(B.21)

B.4 Time-Series Standard Deviation Test (CDA)

Brown and Warner (1980, 1985) used a procedure called “crude dependence adjustments” in which the standard error for this test is computed from the time-series of portfolio mean abnormal returns during the estimation period.

Unlike the standardized abnormal return test, the time-series standard deviation test (CDA: crude dependence adjustment test), uses a single variance estimate for the entire portfolio. Therefore, the time-series standard deviation test does not take into account unequal return variances across securities. In addition, it avoids the potential problem of cross–sectional correlation of security returns. The estimated variance AAR_t is

$$\hat{\alpha}^2_{AAR} = \sum_{t=E_1}^{E_2} \frac{(AAR_t - \overline{AAR})^2}{M-2},$$

(B.22)

where the market-model parameters are estimated over the estimation period of $M = E_2 - E_1 + 1$ days and

$\overline{AAR} = \sum_{t=E_1}^{E_2} \frac{AAR_t}{M}$.

(B.23)

The portfolio test statistic for day t in event time is

$t = \frac{AAR_t}{\hat{\sigma}_{AAR}}$.

(B.24)

Assuming time-series independence, the test statistic for CAR_{T_1,T_2} is

$t = \frac{CAAR_t}{(T_2-T_1+1)^{\frac{1}{2}}\hat{\sigma}_{AAR}}$.

(B.25)

B.5 Cross-Sectional Standard Deviation Test

Brown and Warner (1985), report that the cross-sectional test is well-specified for event date variance but not very powerful. However, Boehmer et al., (1991)report that the standardized cross-sectional test is more powerful and equally well-specified.

The standardized cross-sectional test compensates for a possible variance increase on an event date by incorporating cross-sectional variance adjustments. In the cross-sectional standard deviation test, the daily cross-sectional standard deviation is substituted for the portfolio time-series standard deviation in the non-standardized tests. The portfolio test statistic for day t in event time is

$t = \frac{AAR_t}{\frac{\hat{\sigma}_{AAR}}{\sqrt{N}}}$,

(B.26)

where

$\hat{\alpha}_{AAR}^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(A_{it} - \frac{1}{N}\sum_{i=1}^{N} A_{it}\right)^2$.

(B.27)

The estimated variance of $CAAR_{T_1,T_2}$ is

$\hat{\alpha}_{CAAR_{T_1,T_2}}^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(CAAR_{i,T_1,T_2} - \frac{1}{N}\sum_{i=1}^{N} CAAR_{j,T_1,T_2}\right)^2$.

(B.28)

The test statistic for $CAAR_{T_1,T_2}$ is

$t_{CAAR} = \frac{CAAR_{T_1,T_2}}{\frac{\hat{\alpha}_{CAAR_{T_1,T_2}}^2}{\sqrt{N}}}$.

(B.29)

B.6 Generalized Sign Test[36]

Cowan (1992) notes the generalized sign test controls for the normal asymmetry of positive and negative abnormal returns in the estimation period. The sign test is a simple binomial test of whether the frequency of positive abnormal residuals equals 50%. The generalized sign test is a refined version of this test by allowing the null hypothesis to be different from 0.5. To implement this test, we first need to determine the proportion of stocks in the sample that should have non-negative abnormal returns under the null hypothesis of no abnormal performance. The value for the null is estimated as the average fraction of stocks with non-negative abnormal returns in the estimation period. If abnormal returns are independent across securities, under the null hypothesis, the number of non-negative values of abnormal returns has a binomial distribution with parameter p. The alternative hypothesis, for any level of abnormal performance, is that the proportion is different than that given prior. The advantage of the generalized sign test is that it takes into account the evidence of skewness in security returns. The following statistic has an approximate unit normal distribution:

$$GS = \frac{|P_O - P|}{\sqrt{P(1-P)/_N}},$$

(B.30)

whereP_o is the observed fraction of positive returns computed across stocks in one particular event week, or the average fraction of firms with non-negative abnormal returns for events occurring over multiple weeks.

The null hypothesis for the generalized sign test is that the fraction of positive returns is the same as in the estimation period. The actual test uses the normal approximation of binomial distribution (Sanger and Peterson (1990), Chen, Hu and Shieh (1991).

B.7 Rank Test

The rank test extends to multiple-day windows by assuming that the daily return ranks within the window are independent. The rank test procedure treats the combined estimation period and event period as a single set of returns, and assigns a rank to each day. Let K_{jt} represent the rank abnormal return A_{jt} in the sample $M_j + L_j$ abnormal returns of stock. Let L_j be the number of non-missing returns of stock j in the event period. If there is no missing returns, $L_j = L = Post - Pre + 1$, and $M_j = M = estimation\ period\ length$. Rank one signifies the smallest abnormal return. The mean (median) rank across the combined estimation and event period is

$$\overline{K} = \frac{M+l+1}{2}.$$

(B.31)

The rank test statistic for the event window composed of days T_1 through T_2 is

[36] Dark Side of International Cross Listing - Scribd. (n.d.). Retrieved from http://www.scribd.com/doc/6649803/Dark-Side-of-International-Cross-Listing

$$Z_r = (L)^{\frac{1}{2}} \left\{ \frac{\overline{K_{T_1,T_2}} - \breve{K}}{\left[\sum_{t=1}^{M+1} (\overline{K_t} - \breve{K})^2 / (M+1) \right]^{\frac{1}{2}}} \right\},$$

(B.32)

where

$$\overline{K_{T_1,T_2}} = \frac{1}{L} \sum_{t=T_1}^{T_2} \frac{1}{N} \sum_{j=1}^{N} K_{jt}$$

(B.33)

is the average rank across N stocks and $L = T_2 - T_1 + 1$ days of the event window and $\overline{K_t} = \left(\frac{1}{N}\right) \sum_{j=1}^{N} K_{jt}$ is the average rank across N stocks on day t of the $M + L$ day combined estimation and event period. The expected rank is still $\breve{K}$ for event windows shorter than L days, because the full $M + L$ day set of returns is used for the assignment of ranks.

B.8 Jackknife Test

The Jackknife test (Giaccotto and Sfiridis, 1996) incorporates the standardized abnormal return for each stock, computed using the event period sample standard deviation. The standardized abnormal return for day t is

$$\hat{\theta} = \frac{A_{jt}}{\hat{\sigma}_{A_{jt}}},$$

(B.34)

where

$$\hat{\sigma}_{A_{jt}} = \left\{ \sum_{t=T_1}^{T_2} \frac{(A_{jt} - \overline{A_j})}{L_j} \right\}^{\frac{1}{2}}$$

(B.35)

and $\overline{A_j}$ is the mean abnormal return of stock j during the event period L days. If there is an event-induced, transient variance change on day t, then $\hat{\sigma}_{A_{jt}}$ is a biased estimator of $\sigma_{A_{jt}}$ and $\hat{\theta}$ is a biased statistic. Giaccotto and Sfiridis (1996) purposely reduce the bias by jackknifing the $\hat{\theta}$ values. The first step of the Jackknife is to sequentially delete one abnormal return A_{jT_s} from the equation and re-compute $\hat{\sigma}_{A_{jt}}$, using the new value in turn to re-compute $\hat{\theta}$ using equation. They call the latter value $\hat{\theta}_{(-s)}$. The pseudo-values are

$$\hat{\theta}_{(-s)} = (\ L_j)\hat{\theta} - (\ L_j - 1)\hat{\theta}_{(-s)}.$$

(B.36)

The Jackknife estimator for stock j on day t is the mean of the pseudo-values

$$\hat{\theta}_{jt} = \frac{1}{L_j} \sum_{t=T_1}^{T_2} \hat{\theta}_{(-s)}.$$

(B.37)

To gain efficiency, the estimates are averaged across the sample of stocks:

$$\overline{\Theta_t} = \frac{1}{N}\sum_{j=1}^{N}\theta_{jt}.$$

(B.38)

Finally, the Jackknife test statistic for the sample of stocks on day t is

$$t_{Jackknife} = \frac{\overline{\Theta_t}}{\frac{S_{Jackknife,t}}{\sqrt{N}}},$$

(B.39)

where

$$S_{Jackknife,t} = \left[\frac{1}{N-1}\sum_{i=1}^{N}\left(\hat{\theta}_{jt} - \overline{\Theta_t}\right)^2\right]^{1/2}.$$

(B.40)

The distribution of $t_{Jackknife}$ under the null hypothesis is approximately normal with mean zero and unit variance. To test the significance of the CAAR over the window from date T_1 through T_2, define

$$\hat{\theta}_{T_1,T_2} = \frac{\sum_{t=T_1}^{T_2} A_{jt}}{(T_2-T_1+1)^{\frac{1}{2}}\hat{\sigma}_{A_{jt}}}$$

(B.41)

and sequentially delete one abnormal return A_{jt_s} from equation and re-compute $\hat{\sigma}_{A_{jt}}$, using the new value in turn to re-compute $\ddot{\theta}$ using equation (E.40). Such that, the latter $\hat{\theta}_{(-s),T_1,T_2}$ form the pseudo-values

$$\hat{\theta}_{(-s),T_1,T_2} = (L_j)\hat{\theta}_{T_1,T_2} - (L_j - 1)\hat{\theta}_{(-s),T_1,T_2}.$$

(B.42)

The Jackknife estimator for stock j in window (T_1, T_2) is the mean of the pseudo-values

$$\theta_{T_1,T_2} = \frac{1}{L_j}\sum_{t=T_1}^{T_2}\theta_{(-s)}.$$

(B.43)

The estimates are averaged across the sample of stocks:

$$\overline{\Theta_{T_1,T_2}} = \frac{1}{N}\sum_{j=1}^{N}\theta_{jT_1,T_2}.$$

(B.44)

The Jackknife test statistic for the sample of stocks in window (T_1, T_2) is

$$t_{Jackknife} = \frac{\overline{\Theta_{T_1,T_2}}}{\frac{S_{Jackknife,T_1,T_2}}{\sqrt{N}}},$$

(B.45)

where

$$S_{Jackknife,T_1,T_2} = \left[\frac{1}{N-1}\sum_{i=1}^{N}\left(\theta_{j,T_1,T_2t} - \overline{\Theta_{T_1,T_2}}\right)^2\right]^{1/2}.$$

(B.46)

APPENDIX C

As discussed in Greene (2003), it has been argued that in small samples, White's estimator tends to underestimate the true variance–covariance matrix, resulting in higher *t*-statistic ratios. In other words, using this estimator leads to liberal hypothesis tests involving the least square estimators. Davidson and MacKinnon (1993) offered two alternative versions of this estimator. The HCCME0 option calculates the standard errors based on White's estimator. The HCCME1 option calculates the first alternative suggested by Davidson and MacKinnon. The HCCME2 option calculates the second alternative suggested by Davidson and MacKinnon. The HCCME3 option produces yet another modification of White's estimator.

Table C.1

Obs	_NAME_	_TYPE_	C_Timers	C_BMr1	C_Size	C_lev3	C_ROA
1	C_Timers	OLS	0.000001	–.000000033	0.000000020	0.000000064	0.00000
2	C_BMr1	OLS	0.000000	0.000000078	0.000000007	7.00328E-10	0.00000
3	C_Size	OLS	0.000000	0.000000007	0.000000057	–.000000011	0.00000
4	C_lev3	OLS	0.000000	7.00328E-10	–.000000011	0.000000066	0.00000
5	Const	HCCME0	0.000000	–.000000052	–.000000189	0.000000021	0.00000
6	C_Timers	HCCME0	0.000001	–.000000020	0.000000013	0.000000024	0.00000
7	C_BMr1	HCCME0	0.000000	0.000000012	0.000000003	0.000000003	0.00000
8	C_Size	HCCME0	0.000000	0.000000003	0.000000030	–.000000013	0.00000
9		HCCME1	0.014166	–.002278627	–.005290698	–.003450722	–0.24136
10	Const	HCCME1	0.000000	–.000000052	–.000000189	0.000000021	0.00000
11	C_Timers	HCCME1	0.000001	–.000000020	0.000000013	0.000000024	0.00000
12	C_BMr1	HCCME1	0.000000	0.000000012	0.000000003	0.000000003	0.00000
13	C_ROA	HCCME2	0.000001	0.000000277	–.000000274	0.000000336	0.00003
14		HCCME2	0.014166	–.002278627	–.005290698	–.003450722	–0.24136
15	Const	HCCME2	0.000000	–.000000052	–.000000189	0.000000021	0.00000
16	C_Timers	HCCME2	0.000001	–.000000020	0.000000013	0.000000024	0.00000
17	C_lev3	HCCME3	0.000000	0.000000003	–.000000013	0.000000043	0.00000
18	C_ROA	HCCME3	0.000001	0.000000277	–.000000274	0.000000336	0.00003
19		HCCME3	0.014166	–.002278627	–.005290698	–.003450722	–0.24136
20	Const	HCCME3	0.000000	–.000000052	–.000000189	0.000000021	0.00000
21	C_Timers	HCCME3	0.000001	–.000000020	0.000000013	0.000000024	0.00000
22	C_BMr1	HCCME3	0.000000	0.000000012	0.000000003	0.000000003	0.00000
23	C_Size	HCCME3	0.000000	0.000000003	0.000000031	–.000000013	0.00000
24	C_lev3	HCCME3	0.000000	0.000000003	–.000000013	0.000000043	0.00000
25	C_ROA	HCCME3	0.000001	0.000000277	–.000000274	0.000000336	0.00003

APPENDIX D

IPO Firms That Were Not Included in the Sample.

Name	Symbol	Year	Name	Symbol	Year
Endurance Specialty Holdings Ltd.	ENH	2003	Assured Guaranty Ltd.	AGO	2004
MI Developments Inc.	MIM	2003	CPFL Energia S.A.	CPL	2004
Telkom SA Limited	TKG	2003	DesarrolladoraHomex, S.A.B. de C.V. (Homex)	HXM	2004
Cayman Islands	CTRP	2003	GOL LinhasAéreasInteligentes S.A.	GOL	2004
Cayman Islands	INDM	2003	Herbalife Ltd.	HLF	2004
South Korea	WZEN	2003	LG Display Co., Ltd.	LPL	2004
Bermuda	GLBC	2003	Mechel OAO	MTL	2004
Cayman Islands	LTON	2003	Primus Guaranty, Ltd.	PRS	2004
			RBS Capital Funding Trust VII	RBSPRG	2004
			Cayman Islands	SNDA	2004
			Bermuda	XRTX	2004
			Cayman Islands	KONG	2004
			Marshall Islands	TOPS	2004
			Israel	ELOS	2004
			Puerto Rico	EUBK	2004
			Cayman Islands	JOBS	2004
			Hong Kong	JRJC	2004
			Spain	TLVT	2004
			Cayman Islands	LONG	2004
			Cayman Islands	NINE	2004
			Cayman Islands	NCTY	2004

APPENDIX D (cont.)

IPO Firms That Were Not Included in the Sample.

Name	Symbol	Year
DHT Maritime Inc.	DHT	2005
Diana Shipping, Inc.	DSX	2005
Seaspan Corporation	SSW	2005
Suntech Power Holdings Co., Ltd.	STP	2005
Teekay LNG Partners L.P.	TGP	2005
Marshall Islands	DRYS	2005
Cayman Islands	HRAY	2005
South Korea	GRVY	2005
Israel	SHMR	2005
Cayman Islands	CNTF	2005
Bermuda	NEWL	2005
Bermuda	TBSI	2005
Marshall Islands	EGLE	2005
Cayman Islands	SIMO	2005
Cayman Islands	FMCN	2005
Cayman Islands	BIDU	2005
Cayman Islands	CMED	2005
Netherlands	VPRT	2005
Marshall Islands	GASS	2005
Cayman Islands	VIMC	2005
Cayman Islands	OIIM	2005
Cayman Islands	ACTS	2005
Marshall Islands	FREE	2005
Bermuda	CRMH	2005
Canada	NCST	2005

APPENDIX D (cont.)

IPO Firms That Were Not Included in the Sample.

	Name	Symbol	Year	Name	Symbol	Year
2006	Invesco Ltd.	IVZ	2007	Brookfield Infrastructure Partners L.P.	BIP	2008
2006	LDK Solar Co., Ltd.	LDK	2007	Cascal N.V.	HOO	2008
2006	Longtop Financial Technologies Limited	LFT	2007	Ecopetrol S.A.	EC	2008
2006	MaxcomTelecomunicaciones S.A.B. de C.V.	MXT	2007	Global Ship Lease, Inc.	GSL	2008
2006	Navios Maritime Partners L.P.	NMM	2007	Global Ship Lease, Inc.	GSLU	2008
2006	Noah Education Holdings Ltd.	NED	2007	Global Ship Lease, Inc.	GSLWS	2008
2006	Qiao Xing Mobile Communication Co., Ltd.	QXM	2007	Safe Bulkers Inc.	SB	2008
2006	Simcere Pharmaceutical Group	SCR	2007	Signet Jewelers Limited	SIG	2008
2006	Teekay Tankers Ltd	TNK	2007	TelmexInternacional, S.A.B. DE C.V.	TII	2008
2006	Textainer Group Holdings Limited	TGH	2007	TelmexInternacional, S.A.B. DE C.V.	TIIA	2008
2006	Tongjitang Chinese Medicines Company	TCM	2007	Cayman Islands	ATAI	2008
2006	Triple-S Management Corporation	GTS	2007	Bermuda	MHLD	2008
2006	Validus Holdings, Ltd.	VR	2007	British Virgin Islands	CACAU	2008
2006	VanceInfo Technologies Inc.	VIT	2007	British Virgin Islands	CACA	2008
2006	WSP Holdings Limited	WH	2007	British Virgin Islands	PSOF	2008
2006	WuXiPharmaTech Inc.	WX	2007	Marshall Islands	SHIP	2008
2006	Xinyuan Real Estate Co., Ltd.	XIN	2007			
2006	Marshall Islands	ESEA	2007			
2006	Bermuda	ESGR	2007			
2006	Cayman Islands	SSRX	2007			
2006	Cayman Islands	JASO	2007			
2006	Israel	MLNX	2007			
2006	Israel	ROSG	2007			
2006	Cayman Islands	XSEL	2007			
2006	Marshall Islands	CPLP	2007			
2006	Marshall Islands	OCNF	2007			
2006	Cayman Islands	CSUN	2007			
2006	Netherlands	EURX	2007			
2006	Cayman Islands	GLRE	2007			
2006	Cayman Islands	SPRD	2007			
	Cayman Islands	PWRD	2007			
	Israel	VOLT	2007			
	Bermuda	EXXI	2007			
	Marshall Islands	PRGN	2007			
	British Virgin Islands	FGXI	2007			
	Cayman Islands	CISG	2007			

APPENDIX E

The Following Tables Show Results If Using a Different Market Index Such as Russell 2000

Table E.1: Post-listing Anomaly Does Not Exist (Significant Positive CAAR in the Post-listing Period)

Market Model, -RUSELL(0,+50), Non market timers

Days	*N*	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	Portfolio Time-Series (CDA) t	CSectErr t	Skewness Corrected T1
(-10,-6)	21	-1.09%	-0.59%	10:11	-0.527	-0.560	-0.544	-0.725	-0.759
(-5,-2)	21	-0.48%	-1.24%	8:13	-1.224	-1.470$	-0.267	-0.393	-0.381
(-1,+1)	21	3.90%	1.49%	12:9	1.271	0.639	2.522**	0.989	1.324$
(-3,+3)	21	2.80%	1.09%	10:11	0.566	0.339	1.182	0.677	0.797
(+11,+50)	21	7.24%	9.69%	15:6>>	2.742**	2.414**	1.281	1.406$	1.219

The symbols $,*,, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> etc. correspond to $,* and show the direction and generic one-tail significance of the generalized sign test.**

APPENDIX E (cont.)

The Following Tables Show Results If Using a Different Market Index Such as Russell 2000

Table E.2: Post-listing Anomaly Exist (Significant Negative CAAR in the Post-listing Period)

Market Model, +RUSELL(0,+50), Market timers

Days	*N*	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Patell *Z*	StdCsect *Z*	Portfolio Time-Series (CDA) t	CSectErr t	Skewness Corrected T1
(-10,-6)	10	-4.80%	-1.93%	4:6	-0.636	-0.591	-1.304$	-1.197	-1.542$
(-5,-2)	10	0.09%	1.24%	3:7	0.377	0.321	0.027	0.047	0.049
(-1,+1)	10	5.06%	3.86%	8:2>	1.919*	1.740*	1.773*	2.171*	2.135*
(-3,+3)	10	2.30%	4.00%	6:4	1.184	1.014	0.528	0.598	0.584
(+11,+50)	10	-37.76%	-31.37%	1:9<	-4.315***	-2.552**	-3.625***	-2.676**	-4.078***

The symbols $,*,, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> etc. correspond to $,* and show the direction and generic one-tail significance of the generalized sign test.**

APPENDIX F

The Following Tables Show Robustness Check Using Fama-French Procedure to Estimate the Model

GARCH Estimates			
SSE	11.455287	Observations	36,882
MSE	0.0003106	UncondVar	.
Log Likelihood	167,933.597	Total R-Square	0.9821
SBC	–335,709.46	AIC	–335837.19
MAE	0.21713038	AICC	–335837.18
MAPE	482.592298	Normality Test	4,354,863,551.
		Pr>ChiSq	<.0001
NOTE: No intercept term is used. R-squares are redefined.			

Variable	DF	Estimate	Standard Error	t-value	Approx Pr > $\|t\|$	Variable Label
DTIMERS	**1**	**0.7501***	**0.000575**	**–1,303.9**	**<.0001**	**(Firms that time the market)**
ROA	1	–0.0128	0.000147	–86.65	<.0001	(Return on Assets)
Mkt_RF	1	–0.000023	4.6677E-7	–49.04	<.0001	Mkt-RF
SMB	1	–0.000034	5.5787E-7	–61.08	<.0001	SMB
HML	1	0.0000677	1.1629E-6	58.20	<.0001	HML
AR1	1	–0.6488	0.004663	–139.13	<.0001	
AR2	1	0.0970	0.009352	10.37	<.0001	
AR3	1	–0.4489	0.006284	–71.44	<.0001	
ARCH0	1	1.7566E-6	1.3997E-9	1,255.01	<.0001	
ARCH1	1	3.6171	0.005280	685.06	<.0001	
ARCH2	1	4.0821	0.0369	110.72	<.0001	
ARCH3	1	1.2838	0.1593	8.06	<.0001	
ARCH4	1	20.9833	0.2746	76.40	<.0001	
ARCH5	1	0.4897	0.1205	4.06	<.0001	
ARCH6	1	0.8207	0.1191	6.89	<.0001	

VITA

Moustafa Abu EL Fàdl, Ph.D. Candidate in Finance, CFA

3225 Barrington Dr, Virginia Beach, VA 23452 Ph: 757-472-7027
2160 Constant Hall, Norfolk, VA 23529 (office)
E-mail: mabuelfa@odu.edu

EDUCATION

- **Old Dominion University** **Norfolk, VA, USA**
  The College of Business and Public Administration
- Candidate for the Ph.D. in Finance, August, 2011
  Master in Arts in Economics, Aug. 2009

- **The University of Arizona** **Tucson, AZ, USA**
  The Eller College of Management
  Master of Business Administration, May 2003

- **Ain Shams University** **Cairo, Egypt**
  College of Commerce
  Graduate Diploma (Master's) in Investment Finance, June 1998

- **Helwan University** **Cairo, Egypt**
  College of Commerce and Business Administration
  Bachelorof Commerce and Business Administration, Nov. 1995
- Major: Accounting

- **CFA Institute** **Charlottesville, VA, USA**
  Charter Financial Analyst, Sept. 2009

- **Research Interests**
  International finance: specifically cross listing and market timing
  Event study methodology, investments, investors'psychology

SPECIAL ACHIEVEMENTS

- Won scholarship from USAID to take the M.B.A..at the University of Arizona
- Won scholarship from Old Dominion University to take the Ph.D. inFinance
- Passed Level I, Level II, and Level III of CFA

PUBLICATIONS & CONFERENCES

- Title:"Why Do Companies Cross List? The Post Listing Anomaly Explained,"www.eurojournals.com/irjfe_54_08.pdf (*International Research Journal of Finance and Economics*)
- Title: "Does the Choice of Benchmarks Matter: The Characteristic Index vs. the Market Index,"*American Journal of Social and Management Sciences* ISSN Print: pp. 2156-1540, ISSN Online: pp. 2151–1559
- Title: "Cross-Listing and Earning Management? Evidence from International Cross Listing in USA," (Working paper)
- Discussant at the FMA 2010 conference in New York, and EFA in Denver Jan 2011 and EFMA conference in Portugal, June 2011
- 9th International Conference in Finance in Athens, July 2011. Presented for 30 minutes, followed by discussion