Do IPO Firms Manage Earnings?

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Abstract

IPO literature documents that IPO firms experience a decline in returns after listing. This paper investigates that phenomena and tries to find reasons for it. Earning management studies report that if companies have a high level of discretionary accruals, then those companies engage in earnings management. This paper connects these two literature branches together by using a third part of literature, which is market timing and market efficiency. I built a dummy variable DTIMERS that takes the value of one if the companies time the market and zero 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. The evidence shows the IPO 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 while other IPOs who do not manage earnings achieve significant positive abnormal return in the post-listing period.

Keywords: IPO, Cross-Listing, Market timing, Earning management, Discretionary accruals

1. Introduction

IPO literature documents that firms who issue IPO experience negative abnormal return soon after the issuance. In addition, cross-listing literature documents that firms who cross-list their shares for the first time in USA experience negative post-listing abnormal return.

The recent IPO literature (Clarke et al., 2002; Mikkelsonet al., 1997) recognizes the negative performance after issuance which is inconsistent with efficient market or rational market hypothesis. Cross-listing literature (Merjos (1963, 1967); Sagner and McConnell (1986)), investigated the price behavior of newly-listed stocks and documented that stocks, on average earn positive abnormal returns before listing and negative abnormal returns over the four to six weeks period immediately following listing

Jensen (1986) argues that agency cost may motivate managers to waste free cash flows. Teoh et al., (1998b) documented that issuers use discretionary accruals to report strong earnings relative to actual cash flows which results in buyers paying too high a price for those earnings, therefore, after the event the stock price goes back to its normal levels and that may explain the negative performance after issuance.

In this paper, I argue that managerial motivation is the reason why some companies after they issue their IPOs achieve either a positive abnormal return or a negative abnormal return, therefore, the broad generalization that firms achieve negative abnormal returns after their IPOs is misplaced because some IPOs firms earn positive abnormal returns after listing. In addition, this paper identifies the relationship that can determine the managerial motives and how it is related to the firms IPOs prospects

I formed portfolios of companies that realize significant negative abnormal returns in the post-listing period of (11, +50) while the U.S market (host market) condition is a positive based on the average $S\&P_{500}$ (Note 1) index for the period (0, +50). In addition, I formed portfolios of firms that realize significant positive abnormal returns in the post-listing period of (11, +50) while the U.S market (host market) condition is a negative based on the average $S\&P_{500}$ index for the period (0, +50). I used the discretionary accruals models to test the hypothesis, that managerial motives are the driving factor to post IPOs negative returns or post IPOs positive returns. On one, hand I evaluated the hypothesis that if firms time the market before they cross-list their IPOs, then those firms managers must have a motive of inflating the pre-IPO price for the firms shares, and "therefore", they will also engage in earnings management. On the other hand, if managers do not time the market, then they more than likely not to engage in earnings management. I define that those companies engaging in earnings management have a positive, and significant discretionary accruals while others who are not engaging in earnings management have a negative, and significant discretionary accruals. To conduct the analysis, I created a dummy variable where it is equal to one if companies time the market and zero if they do not.

I employed the current models used in the literature (Note 2) to estimate discretionary accruals. It is widely recognized that the distributions of daily returns indicate heteroscedasticity and autocorrelation; "therefore" I conducted the research with different estimation techniques to correct for both heteroscedasticity and autocorrelation. In addition, I used parametric and non-parametric tests to confirm the validity of the results.

There are various competing explanations have been provided for this anomaly, but there is still lack of consensuses. Kutsuna et al., (2002) reported that the price reversal after IPOs were either from the position of irrational market expectations or managerial timing hypothesis. According to Jensen and Meckling (1976), managerial bias can affect the timing which managers want to list the company shares.

The evidence presented in this paper finds that companies that time the market achieve significant negative post-IPO 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 post-IPO period and they have significant negative contribution to the discretionary accruals; hence they do not engage in earnings management.

This paper contributes to the literature in several ways. First, it challenges the status quo that IPO firms that cross-list will experience negative abnormal returns because the paper proves that there are some companies that achieve positive abnormal returns in post-IPO period. Second, the paper provided a method of determining managerial motives by developing the host market index as a means to distinguish from it managerial motives, as such if the host market is a positive and managers are trying to list their IPO in that opportunity, then that is a reason to believe that the managers motives are market timing and vice versa. Second, this study also proves that managerial motives as proxy by earning management are the main reasons why some firms after their IPO they either obtain negative or positive abnormal returns. Third, this study also proves that managerial motives as proxy by earning management are the main reasons why some firms after their IPO they either obtain negative or positive abnormal returns. Fourth, the study leaves open other research questions such as what is the effect of market timing on the company's prospects.

2. Literature Review

Pagano et al., (2002) examines the aggregate trends in foreign listings, and they find that high-growth European firms that grow quickly without significant leveraging tend to cross-list in the U.S. Ball and Shivakumar (2005) documents that companies who wants to list in the U.S. face a higher reporting level due to enhanced market demand and regulatory incentives. Fuerst (1998) Cheung CS, Lee J (1995), report that firms cross-list in a strong regulatory framework to show their high quality. Doidge et al., (2004) documents those foreign firms who enter in the U.S. market are doing so in order to take advantage of their growth opportunities.

According to Ritter (1984b), earnings are a significant factor in determining the early market values of IPO firms. Bruner et al., (2004) suggest that foreign firms with high quality are able to gain access to the U.S. market but if the operating performance does not reflect the perception of high quality they considered those firms IPOs to be consistent with the ''window-dressing'' concept as mentioned through the work of Teoh et al. (1998) who report that firms adopt discretionary accrual methods to boost their earning, so they look superb for the IPO listing. Nurwati A. and Ahmad-Zaluki (2008) report that there is deterioration in operating performance of IPO companies relative to matching companies following IPOs and that earnings management exists at the time of IPOs due to alteration of pre-IPO accruals. Nurwati A. and Ahmad-Zaluki (2008) documents that lower quality firms are more likely to window-dress. DuCharme, Malatesta, and Sefcik (2004) produce results that support the idea that some firms opportunistically manipulate earnings upward before stock issues. Kahneman et al., (1982) argue that investors are subject to cognitive biases often predict future uncertain events by taking a brief history of information, and when such investors make mistaken beliefs about significant positive accruals that make the market price departs from fundamentals over a period of time. Daniel et al. (1998) report that investors overestimate their knowledge and abilities to build a trading strategy from that information and if they were successful once that will even makes the investors more overconfident about their abilities and such bias he called "self-attribution". According to Daniel et al., 1998 that the self-attribution bias will move the stock price even higher than their intrinsic value. Smith et al., (1997) find that the stock prices of cross-listed firms grow by 8% at the time of listing on U.S. stock exchanges and decline thereafter. Jain and Kini (1994) report that operating performance for post-listing IPO firms decline relative to their pre-IPO levels. Roosenboom et al., (2003) provides evidence in support of IPO price change and reality of earning management. The IPO studies have shown us that after time has passed a price turnaround is more likely to occur, but there is a considerable variation in the stock performance for those IPOs across firms.

Biddle and Saudagaran (1992) find that the tough listing threshold prevents firms from cross-listing on U.S. exchanges. Dechow and Skinner (2000) and Healy et al., (1999), find that firms manage earnings to get cheaper capital, to meet analysts' projections, to fulfill regulatory thresholds, and to increase stock prices. Bailey, Karolyi, and Salva (2006) find that firms who enter in the United States enjoy high returns.

M. Mezhoud and A. Aoubaker (2012) report that there is a window of 30 days trading period where price adjust and there is an underperformance of IPOs for three years after they list. Lang, Lins and Miller (2003) report that firms who cross-list on U.S. exchanges experience higher valuation. Reese and Weisbach (2001) and Lang et al., (2006) suggest that financial statements reporting that is not clear creates an opportunity for foreign firms to manage earnings. Anand et al., (2006) note the first proxy for a company's earnings quality is the common factor identified by factor analysis performed on three measures of earnings quality commonly reported in the literature: accruals quality, earnings variability, and the absolute value of abnormal accruals. Dechow, Sloan, and Sweeney (1996) report 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 an effective 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 decrease in subsequent years. Hence, he concluded that cross-listed firms could be either timing their listings or managing earnings. Lee (1991) 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. DuCharme, Malatesta, and Sefcik (2004) argue that some firms manipulate earnings before stock offerings. Ball and Shivakumar (2006) and Jo and Kim (2007) have produced recent studies suggesting that firms issuing equity can raise their stock price briefly 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. Capital-raising events are a suitable motivation for earnings management, and Teoh et al., (1998a, 1998b); and Erickson and Wang (1999) document that discretionary accruals are used to inflate earnings prior listing.

Carow, Cox, and Roden (2006) provide evidence that manager influence the terms of their firms offer price for the IPO shares. Healy and Wahlen (1999) conclude that some managers inflate reported earnings before public equity offers in order to change investors' expectations of future performance and increase the offer price. Ljungqvist and Wilhelm (2003) find that the percentage of shares allocated to friends and family in internet IPOs is positively related to underpricing, which suggests managerial control in the process. Lowry and Murphy (2006) consider executive stock options issued at the IPO bid price and find no correlation between the options and underpricing and agree that claims of managerial rent-seeking in the literature may be overstated. So one can conclude that the literature is divided on why IPOs net negative or declining returns after they list.

3. Sample and Data

I conducted the research from 2002 to 2009 because this period has the most recent data available and to take advantage of changing market conditions in the U.S. market (host market). The study uses foreign companies that chose to list their IPOs in the U.S. market. The sample included only IPO for foreign companies in order to assess the impact of IPOs and cross-listing event on post-listing returns. Table 1 shows the list of countries used in the sample, their firms daily average return, and the corresponding host market index return ($S\&P_{500}$). Table 1 show that the sample has 2,508 observations with a 0.0041 average daily return for the IPOs companies that listed in the US market.

Table 1.

	Daily Domestic Return			Host Market Index Return		
	Mean	**Std Dev**	**# Obs**	**Mean**	**Std Dev**	**# Obs**
Country						
London	.00016	.01824	30	.30233	.95781	30
Bermuda	.00064	.03296	180	.09242	.78735	198
Canada	.00354	.03269	60	-.0440	1.0345	60
India	.01065	.04430	30	-.0717	.38237	30
Mexico	.00403	.04258	90	.21283	1.0388	120
Israel	.00337	.04631	180	-.0418	.74243	180
KOREA	-.0025	.02392	60	.08900	.49604	60
TAIWAN	.00026	.03203	60	.06000	.44788	60
China	.00719	.12402	1,140	.08559	.74199	1,200
Netherland	.00781	.03467	60	-.0353	.52551	60
Brazil	-.0014	.01522	60	-.0393	.52491	60
Greece	-.0031	.02561	300	.11380	.73073	300
Argentina	.00797	.03603	30	-.0363	.53614	30
SPAIN	.01065	.03637	30	-.0373	.63610	30
COLOMBIA	-.0104	.06506	30	.34733	1.6781	30
Total	.00401	.09015	2,508	.08191	.78805	2,508

I collected 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 Thompson Reuter's database to verify the foreign country and the listing date. I collected post-listing daily prices from the Thomson Reuters database and CRSP daily stock prices tape to confirm it. 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 accumulation of daily stock prices and daily market index method will help determine the daily stock return and the daily market index return, respectively.

IPO literature produced convincing evidence that the listing date is the event date as documented by Lau at el. (1994) who finds that price reactions are most likely to occur on the first trading day and not on either the cross-listing application or compliance dates. Moreover, 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. Therefore, the event date will be the actual IPO listing date.

The sample began with 300 non-U.S. companies that cross-listed their IPOs in the United States either on the NYSE or NASDAQ during the period from 2002 to 2009. The criteria for the pre-listing period are such that the assessment 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 long pre-listing days to have an economically powerful analysis, and for the post-listing period range, I wanted to assure the continuity of the stocks after they do cross-list in order to obtain valid inferences drawn from the analyses. The sample resulted in 89 non-U.S. companies from fifteen different countries. To have an estimate of the normal returns for IPOs firms, I used a matched portfolio of companies as suggested by Brav and Gompers (1997), Carter, Dark, and Singh (1998), Gompers and Lerner (2005).

4. Hypothesis Development

I built on the findings of M. Fadl (2013) that IPO companies who achieve negative abnormal returns after they list are the companies who time the market. I started with forming portfolios of companies that demonstrate market timing behavior and portfolios of companies that do not. According to S. Agarwal, C. Liu, S.G. Rhee (2008), investors have either a high demand or a low demand for certain IPOs offerings, as such, when investors demand is high for some IPOs offerings then those IPOs achieve an initial positive returns but negative in long run and vice versa

I built on those ideas by giving a reason of why investors demand are high for certain IPOs offerings and low in another, as such, when investors know that some companies are timing the market , then they are most likely will manage earnings so investors demands will be low in that instance and vice versa. Table 2 shows that some IPOs companies who cross-list while the U.S. market (host market) condition is a positive (based on the average S&P$_{500}$ index return in the period (0, +50), achieve significant negative abnormal returns (-26.19%) after their IPOs cross-list, particularly in the period (11, +50). The study concludes that since the host market condition is a positive, and the post-listing abnormal return for those companies is a negative then these companies must be timing the market. I reached that conclusion, because why these companies achieved negative post-listing abnormal returns while the U.S. market (host market) is favorable while these companies are supposed to be listing their IPOs because they are expecting positive growth opportunities,. It follows that the market participants have concluded that these companies time the market and discount these companies price after the IPO, which supports hypothesis H_{1A}: Some companies time the market

Table 2. H_{1A}: Some companies time the market

Market Model, +S&P$_{500}$(0,+50)									
Days	N +:-	Mean Cumulative Abnormal Return/ PWCAAR/ Median	Patell Z	StdCsect Z	CSectErr t	Generalized Sign Z	Rank Test Z	Signed Rank	Skewness Corrected T1
(-1,+1)	20 10:10	1.33% 1.96% -0.30%	7.095 (<.001)	0.553 (0.290)	0.470 (0.319)	-0.342 (0.366)	-0.226 (0.411)	6.000 (0.420)	0.498 (0.309)
(-3,+3)	20 9:11	-0.58% 0.39% -0.40%	0.328 (0.372)	0.037 (0.485)	-0.181 (0.428)	-0.791 (0.214)	-2.130 (0.017)	-13.000 (0.324)	-0.180 (0.429)
(+1,+20)	20 1:19<<<	-14.60% -14.13% -12.78%	-22.911 (<.001)	-4.271 (<.001)	-3.770 (<.001)	-4.379 (<.001)	-6.477 (<.001)	-95.000 (<.001)	-5.429 (<.001)
(0,+50)	20 2:18<<<	-34.00% -35.09% -40.50%	-33.227 (<.001)	-5.504 (<.001)	-4.890 (<.001)	-3.931 (<.001)	-8.886 (<.001)	-97.000 (<.001)	-6.512 (<.001)
(+11,+50)	20 5:15<<	-26.19% -28.33% -31.69%	-30.461 (<.001)	-4.458 (<.001)	-4.552 (<.001)	-2.585 (0.005)	-6.940 (<.001)	-87.000 (<.001)	-4.239 (<.001)

P-values are in parentheses. The symbols (,<,<<,<<< or),>,>>,>>> show the direction and generic one-tail significance of the generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

Further, according to Table 3, some companies IPOs cross-list while the host market condition is a negative (based on the average $S\&P_{500}$ index return in the period (0, +50), and yet they achieve significant positive abnormal returns (17.54%) after they cross-list, particularly in the period (11, +50). The study concludes that since the host market condition is a negative and the post-listing abnormal return is a positive then there is no post-listing anomaly. Since that the host market condition cannot explain the positive Cumulative average Abnormal Returns (CAAR) for those companies then these companies do not time the market because they cannot be timing a market that is negative "which supports hypothesis" H_{1B}: Some companies do not time the market.

Table 3. H_{1B}: Some companies do not time the market

Market Model, -S&P500(0,+50)									
Days	**N +:-**	**Mean Cumulative Abnormal Return /PWCAAR /Median**	**Patell Z**	**StdCsect Z**	**CSectErr t**	**Generalized Sign Z**	**Rank Test Z**	**Signed Rank**	**Skewness Corrected T1**
(-1,+1)	13	23.32%	83.905	4.486	4.329	2.303	2.867	41.500	5.637
	11:2>	25.36%	(<.001)	(<.001)	(<.001)	(0.011)	(0.002)	(<.001)	(<.001)
		22.78%							
(-3,+3)	13	24.35%	56.514	3.810	3.443	2.303	0.089	40.500	5.061
	11:2>	26.21%	(<.001)	(<.001)	(<.001)	(0.011)	(0.465)	(0.001)	(<.001)
		19.63%							
(+1,+20)	13	32.52%	43.398	3.532	3.378	1.747	1.731	39.500	4.889
	10:3>	34.35%	(<.001)	(<.001)	(<.001)	(0.040)	(0.042)	(0.002)	(<.001)
		21.62%							
(0,+50)	13	43.71%	35.560	3.536	3.479	1.747	1.469	38.500	4.287
	10:3>	46.16%	(<.001)	(<.001)	(<.001)	(0.040)	(0.071)	(0.002)	(<.001)
		36.94%							
(+11,+50)	13	17.54%	15.612	2.682	2.812	1.191	1.419	30.500	2.868
	9:4	17.71%	(<.001)	(0.004)	(0.002)	(0.117)	(0.078)	(0.016)	(0.002)
		21.99%							

P-values are in parentheses. The symbols (,<,<<,<<< or),>,>>,>>> show the direction and generic one-tail significance of the generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

Table 4 shows that some companies IPOs who cross-list while the host market condition is a positive (based on the average portfolio matching (PM) index return in the period (0, +50), and yet the result is significant negative abnormal returns (-18.87%) after their IPOs cross-list, particularly in the period (11, +50). The study concludes that since the host market condition is a positive and the post-listing abnormal return is a negative (post-listing anomaly), and the host market condition does not explain the anomaly; then those companies time the market, which supports hypothesis H_{2A}: Some companies time the market

Table 4. H_{2A}: Some companies time the market

Market Model, +PM(0,+50)									
Days	**N +:-**	**Mean Cumulative Abnormal Return /PWCAAR/ Median**	**Patell Z**	**StdCsect Z**	**CSectErr t**	**Generalized Sign Z**	**Rank Test Z**	**Signed Rank**	**Skewness Corrected T1**
(-1,+1)	20	-0.22%	-0.926	-0.054	-0.116	0.651	1.270	9.000	-0.116
	12:8	-0.15%	(0.177)	(0.479)	(0.454)	(0.257)	(0.102)	(0.375)	(0.454)
		0.30%							
(-3,+3)	20	-1.50%	-6.457	-0.521	-0.713	0.651	-0.541	-1.000	-0.748
	12:8	-1.39%	(<.001)	(0.301)	(0.238)	(0.257)	(0.294)	(0.493)	(0.227)
		0.65%							
(+1,+20)	20	-7.97%	-27.162	-2.856	-3.017	-2.484	-4.721	-67.000	-3.064
	5:15<<	-9.60%	(<.001)	(0.002)	(0.001)	(0.007)	(<.001)	(0.005)	(0.001)
		-6.96%							
(0,+50)	20	-24.09%	-50.607	-4.820	-4.791	-4.276	-7.115	-103.00	-7.899
	1:19<<<	-29.60%	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
		-16.48%							
(+11,+50)	20	-18.87%	-45.943	-4.321	-4.354	-3.828	-5.956	-95.000	-5.946
	2:18<<<	-23.56%	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
		-13.93%							

P-values are in parentheses. The symbols (,<,<<,<<< or),>,>>,>>> show the direction and generic one-tail significance of the generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

Further, according to Table 5, some companies IPOs cross-list while the host market condition is a negative (based on the average PM index return in the period (0, +50), and yet they achieve significant positive abnormal returns (13.58%)

after they cross-list, particularly in the period (11, +50). The study concludes that since the host market condition is a negative and the post-listing abnormal return is a positive then there is no post-listing anomaly. Since that, the host market condition cannot explain the positive CAAR for those companies; then these companies do not time the market because they cannot be timing a market that is negative. H_{2B}: Some companies do not time the market

Table 5. H_{2B}: Some companies do not time the market

Market Model, -PM(0,+50)									
Days	**N +:-**	**Mean Cumulative Abnormal Return /PWCAAR /Median**	**Patell Z**	**StdCsect Z**	**CSectErr t**	**Generalized Sign Z**	**Rank Test Z**	**Signed Rank**	**Skewness Corrected T1**
(-1,+1)	13	23.12%	159.971	4.379	4.340	2.294	2.029	41.500	5.542
	11:2>	25.39%	(<.001)	(<.001)	(<.001)	(0.011)	(0.021)	(<.001)	(<.001)
		22.56%							
(-3,+3)	13	24.35%	107.654	3.851	3.507	1.738	-0.514	39.500	5.086
	10:3>	26.71%	(<.001)	(<.001)	(<.001)	(0.041)	(0.304)	(0.002)	(<.001)
		19.98%							
(+1,+20)	13	29.90%	76.601	3.378	3.296	1.738	1.358	39.500	4.688
	10:3>	32.68%	(<.001)	(<.001)	(<.001)	(0.041)	(0.087)	(0.002)	(<.001)
		19.48%							
(0,+50)	13	39.43%	61.392	3.378	3.346	1.738	0.703	35.500	3.990
	10:3>	44.08%	(<.001)	(<.001)	(<.001)	(0.041)	(0.241)	(0.005)	(<.001)
		35.60%							
(+11,+50)	13	13.58%	23.759	2.285	2.325	0.627	0.417	27.500	2.399
	8:5	15.81%	(<.001)	(0.011)	(0.010)	(0.265)	(0.338)	(0.029)	(0.008)
		19.89%							

P-values are in parentheses. The symbols (,<,<<,<<< or),>,>>,>>> show the direction and generic one-tail significance of the generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

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 ($CFO_{i,t}$).

$$TOTACC_{i,t} = NI_{i,t} - CFO_{i,t}. \quad (1)$$

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

$$TOTACC_{i,t} = CURRACC_{i,t} + NONECURRACC_{i,t}. \quad (2)$$

I used the second definition (equation 2) of total accruals for my model. 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 ($TA_{i,t}$).

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 other relevant variables. These two variables are designed to capture non-discretionary accruals that may be available. 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.

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_0 \frac{1}{TA_{i,t-1}} + \beta_{1t} \frac{\Delta REV_{i,t}}{TA_{i,t-1}} + \beta_{2t} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \varepsilon_{it}. \quad (3)$$

Dechow, Sloan, and Sweeney (1996) show that the original Jones model has little power in cases in which firms manipulate earnings 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 timely loss recognition. Dechow, Sloan, and Sweeney (1996) report that the modified-Jones model adjusts changes in receivables ($\Delta REC_{i,t}$) in order to control for the manipulation of revenues through using credit sales. Concerns with such misspecification led researchers to adopt performance-matching procedures.

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_{0t}\frac{1}{TA_{i,t-1}} + \beta_{1t}\frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2t}\frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \varepsilon_{it} \ . \quad (4)$$

Kothari, Leone, and Wasley (2005) propose a technique that entails differencing estimates of discretionary accruals from Jones-type models for analysis firms and control firms matched on industry and ROA. However, their results did not produce any significant differences from not using the matching control firms. McNichols (2002) shows models that do not consider long-term earnings growth are particularly susceptible 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 contemporaneous 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 surprising 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 goal of non-discretionary accruals is to correct temporary matching problems with an organization's underlying cash flows, they should be negatively correlated with contemporaneous cash flows and positively correlated with adjacent cash flows. Therefore, they suggest including past, present, and future cash flows (CF) as other relevant variables:

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_{i}\frac{1}{TA_{i,t-1}} + \beta_{1i}\frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i}\frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t}\frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t}\frac{CF_{i,t}}{TA_{i,t-1}} + \frac{CF_{i,t+1}}{TA_{i,t-1}} + \varepsilon_{it}. \quad (5)$$

Ball et al., (2005), and Ball and Shivakumar, (2006), controlled for the non-linearity of accruals with respect to CF 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 CF ($CF_{i,t}$) 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:

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_{i}\frac{1}{TA_{i,t-1}} + \beta_{1i}\frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i}\frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t}\frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t}\frac{CF_{i,t}}{TA_{i,t-1}} + \delta_{2t}\frac{CF_{i,t+1}}{TA_{i,t-1}} + \delta_{3t}\frac{D\Delta CF_{i,t}}{TA_{i,t-1}} + \delta_{3t}\frac{D\Delta CF \times \Delta CF_{i,t}}{TA_{i,t-1}} + \varepsilon_{it}. \quad (6)$$

In this study, I investigate whether there is earnings management in IPOs cross-listing companies that time the market and IPOs cross-listing companies that do not. I will use the model developed by Ball et al. (2006).

$\mathbf{H_0}$: Companies that time the market exhibit earnings management

$\mathbf{H}_{\boldsymbol{A}}$: Companies that do not time the market do not reveal earnings management

5. Research Method

I created a dummy variable DTIMERS that takes the value of one when the portfolios of companies are market timers, and takes a value of zero when the portfolios of companies are non-market timers. Then, I used the discretionary accrual estimates from equation 6 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 different 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 (Note 3) (ABS_DISCACCR) of firms that time the market with firms that do not, these firms were selected based on a predetermined rule regarding the host market condition, 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. Otherwise, when the variances are not assumed to be equal, Satterthwaite method is used. According to Table 6, 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 variance estimator). According to Table 6, panel (A), since the p-value (0.001)—using the Satterthwaite 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.

Table 6. Difference in Means between Market Timers and Non-market Timers (Parametric)

Panel A

Timers	Method	Mean	95% CL Mean		Std Dev	95% CL Std Dev	
Non-Timers		0.0252	0.0248	0.0255	0.0260	0.0258	0.0263
Timers		0.0591	0.0584	0.0597	0.0569	0.0565	0.0574
Diff (1-2)	**Pooled**	-0.0339	-0.0347	-0.0331	0.0461	0.0458	0.0464
Diff (1-2)	**Satterthwaite**	-0.0339	-0.0346	-0.0331			

Panel B

Equality of Variances				
Method	**Num DF**	**Den DF**	**F Value**	**Pr > F**
Folded F	28710	22186	4.79	<.0001

In addition to using parametric tests, I used non-parametric tests because the daily returns distribution is not normally distributed. The Wilcoxon-Mann-Whitney test is a non-parametric analog to the independent samples' t-test. According to Table 7, panel (A), the results suggest there is a statistically significant difference between the underlying distributions of market timers and the non-market timers (z =-81.1443, p = 0.0001). The Mann-Whitney and the corresponding Wilcoxon tests are rank sum tests and not median tests.

Table 7. Difference in Means and Medians between Market Timers and Non-market Timers (Non-parametric)

Panel A:	
Wilcoxon two-sample test	
Statistic	431268330.0000
Normal approximation	
Z	-81.1443
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	

It is possible, for groups to have different rank sums and yet have similar or nearly identical medians. Therefore, I conducted a difference in median tests between market timers and non-market timers. According to Table 7, panel (B), the results suggest there is a statistically significant difference between the underlying distributions of market timers and the non-market timers (z = -63.4016, p = 0.0001).

Panel B:	
Median Two-Sample Test	
Statistic	7555.0000
Z	-63.4016
One-Sided Pr < Z	<.0001
Two-Sided Pr > |Z|	<.0001

Table 7: Panel C:	
Median One-Way Analysis	
Chi-Square	4019.7657
DF	1
Pr > Chi-Square	<.0001

After I established that there was 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 process as follows:

First, I estimated the total accruals using the following equation: (Note 4)

$$\frac{TOTACC_{i,t}}{TA_{i,t-1}} = \alpha_i \frac{1}{TA_{i,t-1}} + \beta_{1i} \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t} \frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t} \frac{CF_{i,t}}{TA_{i,t-1}} + \delta_{2t} \frac{CF_{i,t+1}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF_{i,t}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF \text{ x } \Delta CF_{i,t}}{TA_{i,t-1}} + \varepsilon_{it}. \quad (7)$$

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

$$DISCACCR_{i,t} = \frac{TOTACC_{i,t}}{TA_{i,t-1}} - \alpha_i \frac{1}{TA_{i,t-1}} + \beta_{1i} \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_{2i} \frac{\Delta PPE_{i,t}}{TA_{i,t-1}} + \delta_{0t} \frac{CF_{i,t-1}}{TA_{i,t-1}} + \delta_{1t} \frac{CF_{i,t}}{TA_{i,t-1}} + \delta_{2t} \frac{CF_{i,t+1}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF_{i,t}}{TA_{i,t-1}} + \delta_{3t} \frac{D\Delta CF \text{ x } \Delta CF_{i,t}}{TA_{i,t-1}} \quad (8)$$

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 (Note 5) I used the following regression model:

$$\left|DISCACCR_{i,t}\right| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + Leverage_{i,t} + BM_{i,t}$$

Where

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

$Dtimers_{i,t}$ = a dummy variable that takes the value of one when companies time the market and the value of zero 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 companies (is the natural log of total assets)

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

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

Before I started using the model, I tested for interaction among independent variable by using the Pearson correlation coefficients. These numbers measure the magnitude and direction of the linear relationship between the variables. Under H_0: Rho= 0 that the correlation (Rho) is zero. According to Table 8, 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 actually 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 strong.

Table 8. Correlation Coefficients between Independent Variables

Panel A

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
Size	38623	5.50707	1.89670	212700	0.45742	10.05202
BM	29463	0.92279	2.23312	27188	0.01019	41.15385
ROA	51388	3.79927	14.68611	195237	-46.04000	105.88000
Leverage	38623	0.55619	1.09114	21482	0	7.84177
Size	38623	5.50707	1.89670	212700	0.45742	10.05202
Timers	77484	0.60606	0.48862	46960	0	1.00000

Panel B

Pearson Correlation Coefficients Prob > |r| under H0: Rho=0 Number of Observations	Size	BM	ROA	Leverage	Size	Timers
Size (Size)	1.00000	-0.06826 <.0001	-0.01301 0.0242	0.10313 <.0001	1.00000	-0.04530 <.0001
BM (Book-to-Market Ratio)	-0.06826 <.0001	1.00000	-0.03628 <.0001	0.16200 <.0001	-0.06826 <.0001	0.25865 <.0001
ROA	-0.01301 0.0242	-0.03628 <.0001	1.00000	-0.11473 <.0001	-0.01301 0.0242	0.08975 <.0001
Leverage (Leverage)	0.10313 <.0001	0.16200 <.0001	-0.11473 <.0001	1.00000	0.10313 <.0001	0.03017 <.0001
Size (Size)	1.00000	-0.06826 <.0001	-0.01301 0.0242	0.10313 <.0001	1.00000	-0.04530 <.0001
Timers (Companies Timing the Market)	-0.04530 <.0001	0.25865 <.0001	0.08975 <.0001	0.03017 <.0001	-0.04530 <.0001	1.00000

* Significant at the 5% level.

6. Regression Diagnostics and Hypothesis Results

One of the main assumptions of the Ordinary Least Square (OLS) regression is the homogeneity of variance of the residuals. A commonly used graphical design is to plot the residuals versus predicted values. Figure 1 shows the structure of the data points widening toward the right side, which is an indication of mild heteroscedasticity.

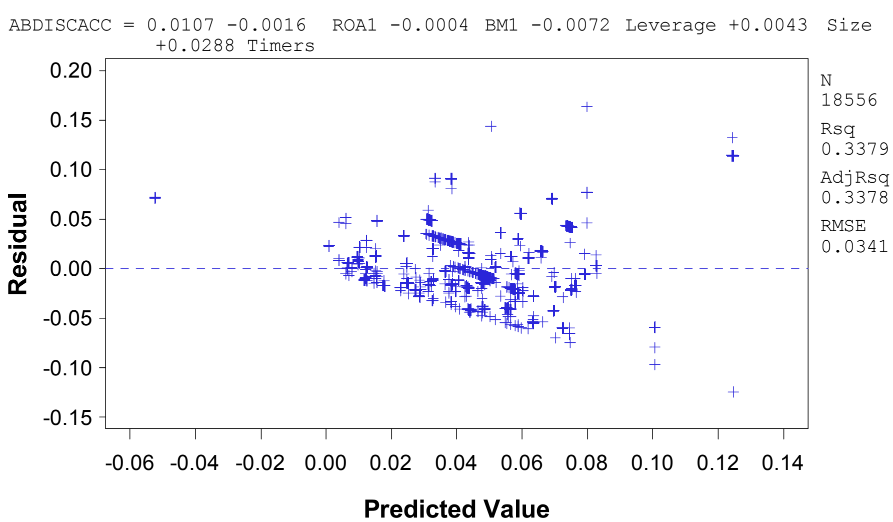

Figure 1.

I ran diagnostic statistics on my regression model:

$$\left|DISCACCR_{i,t}\right| = Dtimers_{i,t} + ROA_{i,t} + Size_{i,t} + Leverage_{i,t} + +BM_{i,t}$$

According to Table 9, panel (A), the F statistic = 1893.67, with a p-value < (0.0001), that means the independent variables are not all equal, and they are significantly different from zero. Table 9, panel (B) shows the parameter estimates and the dummy variable *DTIMERS* are positive and significant at the (0.05) significance level, which suggests that companies that time the market are 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 warrant further investigation. I explain tolerance as 1/VIF, to check on the degree of collinearity, and as such, tolerance values lower than 0.1 is equivalent to a VIF of 10. It means that the variable could be considered as a linear combination of other independent variables. I also eliminate the intercept from those calculations, but it is still included in the calculation of the regression. Table 9, panel (B) shows that, the VIF for all the independent variables is less than two and tolerance is less than 1, which means we do not have a case of complete multicollinearity. To investigate 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 9 panel (C) contains the Eigenvalues of the regressors and they are ranked from highest to lowest. As long as no significant differences are evident among the Eigenvalues (large variability), then there is no strong degree of multicollinearity. Freund and Littell (2000) and Myers (1990), report that small Eigenvalues represent near-perfect linear dependencies or high multicollinearity. According to Table 9, panel (C), the Eigenvalues corresponding to the independent variables are not particularly 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. According to Myers (1990) since the condition number for the independent variables are not high, then they do not have a high degree of multicollinearity. Table 9, panel (C) shows that the condition numbers for the independent variables are between 1 and 1.9, indicating a remarkably mild case of multicollinearity. The White exam tests the null hypothesis that the variance of the residuals is homogenous. According to Table 9, panel (D), since the p-value is extremely small (<0.001), I will reject the hypothesis of homoscedasticity and accept the alternative hypothesis that the variance is not homogenous.

Table 9. Regression Diagnostic for the Model (cont)

$$\left|ADISCACCR_{i,t}\right| = Dtimers_{i,t} + ROA_{i,t} + BM_{i,t} + Leverage_{i,t} + Size_{i,t}$$

Panel A

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	11.03839	2.20768	1893.67	<.0001
Error	18550	21.62596	0.00117		
Corrected Total	18555	32.66435			

Panel B

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	Tolerance	Variance Inflation
Intercept	0.01072	0.00111	9.68	<.0001	.	0
ROA	-0.00157	0.00001896	-83.05	<.0001	0.89799	1.11360
BM	-0.00038102	0.00011380	-3.35	0.0008	0.91659	1.09101
Leverage	-0.00723	0.00035403	-20.43	<.0001	0.94276	1.06072
Size	0.00435	0.00018326	23.71	<.0001	0.88276	1.13281
Timers	0.02880	0.00052236	55.14	<.0001	0.92999	1.07528

Panel C.

Collinearity Diagnostics (intercept adjusted)							
Number	Eigenvalue	Condition Index	Proportion of Variation				
			ROA	BM	Leverage	Size	Timers
1	1.37670	1.00000	0.25380	0.00497	0.01101	0.25545	0.12765
2	1.22521	1.06002	0.04708	0.42349	0.17753	0.02220	0.08209
3	1.04639	1.14702	0.00271	0.02045	0.47633	0.09168	0.29874
4	0.72533	1.37769	0.52395	0.24544	0.01765	0.13058	0.33552
5	0.62637	1.48253	0.17246	0.30565	0.31748	0.50009	0.15599

Panel D

Test of First and Second Moment Specification		
DF	Chi-Square	Pr > ChiSq
20	2909.54	<.0001

Since I rejected the hypothesis of homoscedasticity, then I want to determine the asymptotic covariance matrix of the estimates under the hypothesis of heteroscedasticity. Table 10 Panels (B) and (C) show that the point estimates of the coefficients are exactly the same as in ordinary OLS—as shown in Table 10, 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).

Table 10. Robust Standard Error Regression Model

$$\left|ADISCACCR_{i,t}\right| = Dtimers_{i,t} + ROA_{i,t} + BM_{i,t} + Leverage_{i,t} + Size_{i,t}$$

Panel A

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	11.03839	2.20768	1893.67	<.0001
Error	18550	21.62596	0.00117		
Corrected Total	18555	32.66435			
Root MSE		0.03414	**R-Square**		0.3379
Dependent Mean		0.04318	**Adj R-Sq**		0.3378
Coeff Var		79.07356			

Panel B

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	Heteroscedasticity Consistent		
					Standard Error	t Value	Pr > |t|
Intercept	0.01072	0.00111	9.68	<.0001	0.00114	9.41	<.0001
ROA	-0.00157	0.00001896	-83.05	<.0001	0.00003200	-49.20	<.0001
BM	-0.00038102	0.00011380	-3.35	0.0008	0.00007052	-5.40	<.0001
Leverage	-0.00723	0.00035403	-20.43	<.0001	0.00025551	-28.31	<.0001
Size	0.00435	0.00018326	23.71	<.0001	0.00018300	23.75	<.0001
Timers	0.02880	0.00052236	55.14	<.0001	0.00054753	52.60	<.0001

Panel C

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	ROBUST_STDERR	TVALUE_RB
Intercept	0.01072	0.00111	9.68	<.0001	0.001146	9.353653
ROA	-0.00157	0.00001896	-83.05	<.0001	0.000032	-48.8892
BM	-0.00038102	0.00011380	-3.35	0.0008	0.000071	-5.36851
Leverage	-0.00723	0.00035403	-20.43	<.0001	0.000257	-28.1257
Size	0.00435	0.00018326	23.71	<.0001	0.000184	23.59633
Timers	0.02880	0.00052236	55.14	<.0001	0.000551	52.26718

7. Robustness Check

7.1 Detecting and Correcting for Heteroscedasticity

Since I established that the data suffer from heteroscedasticity, and Verbeek (2004) notes there are regular tests for detecting the presence of non-spherical disturbances: White's standard test, the Goldfeld-Quand t-test, and the Breusch-Pagan test.

To conduct the investigation; first, I define the parameters of the model as Const (for the intercept), C_Timers (TIMERS), C_BM (BM), C_Size (Size), C Leverage (Leverage), C_ROA (ROA). I will be regressing ABS_DISCACRR against Timers, BM, Size, Leverage, and ROA. Table 11, panel (C) shows that the test-statistic value for White's test has a p-value equal (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.

Table 11. Testing for Heteroscedasticity in the Regression Model

$$\left|ADISCACCR_{i,t}\right| = Dtimers_{i,t} + ROA_{i,t} + BM_{i,t} + Leverage_{i,t} + Size_{i,t}$$

Panel A

The Equation to Estimate is							
ABDISCACC =	F(Const(1), C_ROA(ROA), C_BM(BM), C_Leverage(Leverage), C_Size(Size), C_Timers(Timers))						
Nonlinear OLS Summary of Residual Errors							
Equation	**DF Model**	**DF Error**	**SSE**	**MSE**	**Root MSE**	**R-Square**	**Adj R-Sq**
ABDISCACC	6	18550	21.6260	0.00117	0.0341	0.3379	0.3378

Panel B

Nonlinear OLS Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
Const	0.010718	0.00111	9.68	<.0001
C_ROA	-0.00157	0.000019	-83.05	<.0001
C_BM	-0.00038	0.000114	-3.35	0.0008
C_Leverage	-0.00723	0.000354	-20.43	<.0001
C_Size	0.004346	0.000183	23.71	<.0001
C_Timers	0.0288	0.000522	55.14	<.0001

Panel C

Heteroscedasticity Test					
Equation	**Test**	**Statistic**	**DF**	**Pr > ChiSq**	**Variables**
ABDISCACC	White's Test	9103	19	<.0001	Cross of all vars
	Breusch-Pagan	4371	2	<.0001	1, Timers, ROA

To compute the generalized least squares (GLS) estimator, first, I must alter the response variable, second calculate the weighted explanatory variables according to Greene (2003) and Verbeek (2004. Until now the assumption was 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 take too many parameters, and it will be difficult to estimate. However, according to Green (2003) and Verbeek (2004), 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 either use the two-step FGLS technique or use the maximum likelihood estimation. I will use the two-step FGLS estimator.

The analysis results are given in Table 12. I estimated FGLS by applying the idea that the variance of the disturbances is proportional to the expected value of the residual of the vector parameter. Table 12, panel (B) shows that DTIMERS with t-statistic of 45.26 and p-value of <0.0001 is still positive and significant at the 0.05 significance level.

Table 12. Using FGLS to Estimate the Regression Model

Weight: 1/exp (pred)

$$\left|ADISCACCR_{i,t}\right| = Dtimers_{i,t} + ROA_{i,t} + BM_{i,t} + Leverage_{i,t} + Size_{i,t}$$

Panel A

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	5	17439	3487.80970	1164.51	<.0001
Error	18550	55559	2.99509		
Corrected Total	18555	72998			
Root MSE	1.73063	**R-Square**			0.2389
Dependent Mean	0.03656	**Adj R-Sq**			0.2387
Coeff Var	4733.95353				

Panel B

Variable	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	0.01533	0.00099132	15.46	<.0001
ROA	-0.00123	0.00002171	-56.46	<.0001
BM	0.00020204	0.00009576	2.11	0.0349
Leverage	-0.00713	0.00028273	-25.20	<.0001
Size	0.00382	0.00015513	24.63	<.0001
Timers	0.01967	0.00043453	45.26	<.0001

Enders (2004) postulated time-series variance is cont constant, and Greene (2003) when the variance of the disturbance is assumed to depend on the variance of the disturbance in the previous time periods, then the time-series is hterosecasdictic. Engle's (1982) autoregressive, conditionally heteroscedastic models (ARCH) assumes hetrosecasdictic variance. He proposed a methodology where the variances of the disturbances are not constant and depend on its past.

The simplest form of Engle's ARCH model is the ARCH (1) model. To test for ARCH effect the Lagrange Multiplier test (LM) is 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 15, panel (A) show the values for SSE and MSE, which are for the error and mean sums of squares, respectively. The MSE is the unconditional variance of the series. The Durbin-Watson statistic is used to test for serial correlation. 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 13, 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 the test is highly significant across the twelve lag windows. The LM statistic is highly significant across all twelve lags indicating that a higher order ARCH process will be appropriate to model the data.

Table 13. Testing for ARCH Process

Panel A

Dependent Variable	ABDISCACC		
	Ordinary Least Squares Estimates		
SSE	122.459994	**DFE**	50897
MSE	0.00241	**Root MSE**	0.04905
SBC	-162451.38	**AIC**	-162460.21
MAE	0.07091067	**AICC**	-162460.21
MAPE	1.5999E14	**Regress R-Square**	0.0000
Durbin-Watson	0.0119	**Total R-Square**	0.0000

Panel B

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	49843.8143	<.0001	49840.8778	<.0001
2	99363.2883	<.0001	49964.2755	<.0001
3	148509.792	<.0001	49974.7487	<.0001
4	197283.733	<.0001	49975.5736	<.0001
5	245686.523	<.0001	49975.6218	<.0001
6	293719.570	<.0001	49975.6222	<.0001
7	341384.286	<.0001	49975.6235	<.0001
8	388682.082	<.0001	49975.6261	<.0001
9	435614.366	<.0001	49975.6293	<.0001
10	482182.552	<.0001	49975.6326	<.0001
11	528388.048	<.0001	49975.6360	<.0001
12	574232.266	<.0001	49975.6394	<.0001

Bollerslev (1986) extended the ARCH, and the result is the generalized autoregressive conditional heteroscedastic model or GARCH. Baltagi (2008) 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. Greene (2003) reports that the MLE can be used to estimate the parameters of both the ARCH and GARCH models. The analysis results are given in Table 14 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. $ARCH_0$ gives the estimate ofα_0, $ARCH_1$ gives the estimate ofα_1, and GARCH1 gives the estimate ofβ_1.

Table 14. Testing for GARCH Process

Panel A

Dependent Variable	ABDISCACC		
	Ordinary Least Squares Estimates		
SSE	122.459994	**DFE**	50897
MSE	0.00241	**Root MSE**	0.04905
SBC	-162451.38	**AIC**	-162460.21
MAE	0.03545534	**AICC**	-162460.21
MAPE	1.5999E14	**Regress R-Square**	0.0000
Durbin-Watson	0.0119	**Total R-Square**	0.0000

Panel B

Variable	**DF**	**Estimate**	**Standard Error**	**t Value**	**Approx r > |t|**
Intercept	1	0.0443	0.000217	203.69	<.0001
		GARCH Estimates			
SSE		165.898982	**Observations**		50898
SBC		-275634.11	**AIC**		-275669.46
MAE		0.03413364	**AICC**		-275669.46
MAPE		5.44527E13	**Normality Test**		2989434.15
			Pr > ChiSq		<.0001

The output indicates that there is strong evidence of GARCH effects (p value <0.0001).

Panel C

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0151	2.5103E-6	6004.55	<.0001
ARCH0	1	2.4298E-7	1.2791E-9	189.96	<.0001
ARCH1	1	0.4967	0.001828	271.70	<.0001
GARCH1	1	0.5040	0.001831	275.29	<.0001

(pvalue <0.0001), which indicates that the residuals from the GARCH model are not normally distributed

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 15, panel (B) shows that ARCH (5) the t-statistic is (2.66) with a p-value (0.0078), which renders ARCH (5) significant. Moreover, GARCH (1) with a t-statistic (0.51) with a p-value (0.6076) renders GARCH (1) insignificant. The above analysis leads to the assumptions that there is a high degree of autocorrelation

Table 15. Using ARCH (5) and GARCH (2) to Estimate the Regression Model

$$\left|ADISCACCR_{i,t}\right| = Dtimers_{i,t} + ROA_{i,t} + BM_{i,t} + Leverage_{i,t} + Size_{i,t}$$

Panel A

GARCH Estimates			
SSE	34.1807571	**Observations**	18556
MSE	0.00184	**Uncond Var**	.
Log Likelihood	54889.3382	**Total R-Square**	.
SBC	-109641.08	**AIC**	-109750.68
MAE	0.02672774	**AICC**	-109750.65
MAPE	2.20345E13	**Normality Test**	1993885.76
		Pr > ChiSq	<.0001

Panel B

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.003686	0.0000120	307.50	<.0001
ROA	1	-0.000412	2.4267E-7	-1699.7	<.0001
BM	1	0.001502	7.889E-6	190.33	<.0001
Leverage	1	-0.007340	7.7514E-6	-946.91	<.0001
Size	1	0.004716	1.8807E-6	2507.44	<.0001
Timers	1	-0.002076	7.9254E-6	-261.99	<.0001
ARCH0	1	6.1469E-7	1.2316E-8	49.91	<.0001
ARCH1	1	0.2073	0.003284	63.12	<.0001
ARCH2	1	0.1973	0.0294	6.71	<.0001
ARCH3	1	0.1944	0.0857	2.27	0.0233
ARCH4	1	0.1930	0.0970	1.99	0.0466
ARCH5	1	0.1915	0.0720	2.66	0.0078
GARCH1	1	0.0101	0.0196	0.51	0.6076
GARCH2	1	0.006789	0.008647	0.79	0.4324

7.2 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 ineffective and will have incorrect standard errors. Estimation techniques under the notion of serial correlation parallel the estimation methods for heteroscedasticity. That is an estimate of the variance–covariance matrix is needed. The GLS estimator can be calculated using the Prais-Winsten transformations by using the variance and covariance, matrix of the disturbances. 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 exceedingly 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 16, panel (B) reveals that the DW statistic of 0.0211 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.

Table 16. Testing for Auto Correlation

Panel A

Ordinary Least Squares Estimates			
SSE	21.6259607	**DFE**	18550
MSE	0.00117	**Root MSE**	0.03414
SBC	-72620.741	**AIC**	-72667.713
MAE	0.0261328	**AICC**	-72667.708
MAPE	3.56131E13	**Regress R-Square**	0.3379
Durbin-Watson	0.0211	**Total R-Square**	0.3379

Panel B

Durbin-Watson Statistics			
Order	**DW**	**Pr < DW**	**Pr > DW**
1	0.0211	<.0001	1.0000

Panel C

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	18164.0022	<.0001
AR(2)	18195.1047	<.0001
AR(3)	18196.9657	<.0001
AR(4)	18197.0637	<.0001

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. I ran a back-step regression where the model eliminates the lags that have an insignificant t-statistic. Table 17, panel (A) reports an estimate of the first three order autocorrelations, and as it shows, they are all significant. Panel (B) reports the results of the back-step regression model where lag 1, 2, and has a t-statistic of -88.99, -29.35, and -12.69, respectively, and they are all significant. The results imply that the autoregressive model should be of a high order and probably between 10 and 14.

Table 17. Back-step Regression to Determine the Degree of the AR Process

Panel A

<table>
<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>0.00117</td><td>1.000000</td><td>| |********************|</td></tr>
<tr><td>1</td><td>0.00115</td><td>0.990373</td><td>| |********************|</td></tr>
<tr><td>2</td><td>0.00115</td><td>0.986849</td><td>| |********************|</td></tr>
<tr><td>3</td><td>0.00115</td><td>0.983037</td><td>| |********************|</td></tr>
</table>

Panel B

Estimates of Autoregressive Parameters			
Lag	**Coefficient**	**Standard Error**	**t Value**
1	-0.650646	0.007311	-88.99
2	-0.250598	0.008538	-29.35
3	-0.092762	0.007311	-12.69
		Yule-Walker Estimates	
SSE	0.34105422	**DFE**	18547
MSE	0.0000184	**Root MSE**	0.00429
SBC	.	**AIC**	.
MAE	0.00053635	**AICC**	.
MAPE	1.77291E13	**Regress R-Square**	0.0230
		Total R-Square	0.9896

Panel C

Durbin-Watson Statistics			
Order	**DW**	**Pr < DW**	**Pr > DW**
1	1.6493	<.0001	1.0000
2	1.9019	<.0001	1.0000
3	2.0069	0.6858	0.3142

The next step is to re-estimate the model while adjusting for both autocorrelations using an AR order of fourteen and adjusting for heteroscedasticity using the GARCH method of an order (q = 3). The FGLS estimates are then reported, assuming the AR (14) model, and GARCH (q = 3). Table 18, panel (C) shows the final estimate of the model after using AR(14) and GARCH (q = 3) and reports that DTIMERS has a t-statistic of 3.66 with a p-value of <0.0003, which is highly positive and significant, and confirms that companies that time the market engage in earnings management. Panel (C) also reports that AR5 with a p-value 0.8233 is insignificant at the 0.05 level and that ARCH (2) and GARCH (1) are both insignificant with a p-value (1.000). The above analysis proves that after adjusting for autocorrelation and heteroscedasticity the portfolio of companies who time the market that is the companies who cross-list their IPO while the host market is a positive then these companies are more likely to engage in earning management. The analysis explain why these firms achieved negative abnormal returns post their IPOs while other firms who did not time the market achieve positive abnormal returns post their IPOs.

Table 18. AR (14) and GARCH (3) Are Used to Estimate the Regression

Panel A

Estimates of Autoregressive Parameters			
Lag	**Coefficient**	**Standard Error**	**t Value**
1	-0.648102	0.007345	-88.24
2	-0.243829	0.008753	-27.86
3	-0.075037	0.008934	-8.40
4	-0.022427	0.008951	-2.51
5	-0.006806	0.008952	-0.76
6	-0.002069	0.008953	-0.23
7	0.000000588	0.008953	0.00
8	-0.000327	0.008953	-0.04
9	0.000138	0.008953	0.02
10	0.000404	0.008952	0.05
11	-0.001719	0.008951	-0.19
12	0.004001	0.008934	0.45
13	0.000409	0.008753	0.05
14	0.001302	0.007345	0.18

Panel B

GARCH Estimates			
SSE	0.33039359	**Observations**	18248
MSE	0.0000181	**Uncond Var**	9.32022E-6
Log Likelihood	74968.4508	**Total R-Square**	0.9899
SBC	-149701.42	**AIC**	-149888.9
MAE	0.00049712	**AICC**	-149888.84
MAPE	1.73594E13	**Normality Test**	323037372
		Pr > ChiSq	<.0001

Panel C

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.1253	0.000372	336.93	<.0001
ROA1	1	-0.000125	1.9075E-6	-65.62	<.0001
BM1	1	-0.000161	0.0000251	-6.41	<.0001
Leverage	1	0.000492	0.0000886	5.56	<.0001
Size	1	-0.0177	0.000103	-171.71	<.0001
Timers	1	0.0297	0.008129	3.66	0.0003
AR1	1	-0.6482	0.001140	-568.61	<.0001
AR2	1	-0.2439	0.002131	-114.47	<.0001
AR3	1	-0.0751	0.004806	-15.63	<.0001
AR4	1	-0.0225	0.0120	-1.88	0.0605
AR5	1	-0.006889	0.0308	-0.22	0.8233
AR6	1	-0.002153	0.0537	-0.04	0.9680
AR7	1	-0.000083	0.0686	-0.00	0.9990
AR8	1	-0.000411	0.0702	-0.01	0.9953
AR9	1	0.0000540	0.0685	0.00	0.9994
AR10	1	0.000320	0.0667	0.00	0.9962
AR11	1	-0.001804	0.0594	-0.03	0.9758
AR12	1	0.003914	0.0460	0.09	0.9322
AR13	1	0.000323	0.0550	0.01	0.9953
AR14	1	0.001216	0.0472	0.03	0.9794
ARCH0	1	9.2964E-6	0.0000593	0.16	0.8755
ARCH1	1	0.002186	6.6597E-6	328.24	<.0001
ARCH2	1	0.000363	0.0137	0.03	0.9789
ARCH3	1	-8.6E-9	0.003477	-0.00	1.0000
GARCH1	1	6.7318E-6	6.2764	0.00	1.0000
GARCH2	1	2.815E-6	1.1880	0.00	1.0000

8. Summary and Concluding Remarks

Some IPOs companies' cross-list their shares in a host market, while that host market is up, whereas other IPOs companies cross-list their shares regardless of market conditions. The IPOs literature reports that IPOs companies who cross-list in foreign market are doing so to signal their positive prospects; however, those companies achieve negative abnormal returns after their IPOs. I used the $S\&P_{500}$ market index to condition for the host market condition and used the same market index to estimate the abnormal returns. I found that some IPOs companies that cross-list while the U.S. market (host market) is up, these companies achieve significant negative abnormal returns while others who cross-list their IPOs while the U.S. market (host market) is down, these companies achieve significant positive abnormal returns. If the firms that cross-list their IPOs shares while the U.S. market (host market) is up and achieve significant negative abnormal returns, then these companies are timing the market while others who cross-list their IPOs shares while the market is down they do not time the market.

Further, this paper 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 dummy variable DTIMERS that takes the value of one if the companies time the market and zero 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 paper 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 has 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 IPOs 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 IPOs cross-listing companies without conducting due diligence, and financial analysts must not issue a recommendation to buy an IPO firm that cross-lists unless they have examined the timing of IPOs 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.

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Notes

Note 1. I used the S&P500 as the benchmark index to estimate and calculate the abnormal returns.

Note 2. See the literature review for further elaboration on the subject.

Note 3. More discussion on this variable is found on the next page.

Note 4. More discussion on the equation can be found in the section on hypothesis development.

Note 5. See the section on previous research and hypothesis development.