



Short-term Overreaction in American Depository Receipts

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Abstract

In this paper we examine for the first time the short-term predictability of American Depository Receipts (ADRs) in reaction to extreme price movements. Based on an analysis of 2,911 extreme price movements that took place within either normal trading hours or after-hours in the period 2001-2019, we conclude that those extreme returns were on average followed by significant reversals. This response represents an overreaction in prices, which challenges the weak version of the efficient market hypothesis. Price reversals are especially pronounced following extreme returns observed during after-hours, which lends support to the assertion that ADR markets are particularly inefficient during this trading period. These findings carry important implications for both market practitioners and regulators.

Keywords: American Depository Receipts; overreaction; market efficiency; short-term reversal.

JEL classification: G11; G14; G15.

1. INTRODUCTION

American Depository Receipts (ADR) programs have been growing in number during the past decades at an impressive pace. Over the 2018-2019 period alone, 177 new programs were launched. According to the Bank of New York Mellon, there are now more than 3,000 ADR programs worth 150.3 billion USD and the trading value of ADRs listed on US exchanges at the end of 2019, totaled the astonishing figure of 3.3 trillion USD.

ADRs are negotiable certificates representing ownership of the securities of a non-US resident corporation. ADRs play a very important role in the global financial markets since they are one of the most common ways by which American investors may diversify their portfolios internationally. Moreover, they bring for investors the advantages of liquidity and convenience of trading shares in US markets issued by companies located in non-US markets. ADRs also present important advantages for the firms based outside of the US because they enable them to sell their equity in the US market in a form more readily acceptable to US investors.

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Given the economic importance of ADR programs, it is surprising that so scarce attention has been paid in the literature to the price dynamics in this market. Finding any systematic pattern in the behavior of financial prices is an important matter that has attracted scholars' attention during the last decades. For example, the short-term predictability after extreme shocks has been studied in a number of different assets such as stock market indices, stocks, bonds, derivatives, ETFs and mutual funds (Fung *et al.*, 2000; Fuertes and Thomas, 2006; Nam *et al.*, 2006; Kassimatis *et al.*, 2008; Mazouz *et al.*, 2012; Lobão and Costa, 2020). However, to the authors' knowledge, there are no studies addressing the short-term reaction of ADR prices to extreme price shocks.

In this paper we fill this gap by examining the short-term response to the changes in the price of ADRs that occur during either normal trading hours and after-hours. We analyze 2,911 extreme price movements of ADRs in the period 2001-2019, comparing the normal hours returns ("open-to-close") and after-hours returns ("close-to-open") for a set of 127 ADRs. We also divide our sample by ADR sector and carry out a multivariate analysis to determine which factors may explain the existence of price under/overreaction immediately after extreme price shocks.

Our results show that, on average, an extreme price movement in ADRs is followed by a significant reversal. This pattern of predictability is common to the normal hours and after-hours periods but the reversal of the extreme price shocks that take place in the latter period is significantly stronger. These results are robust to the introduction of a large set of control variables in the analysis. Overall, our evidence indicates that ADR prices exhibit a significant overreaction, especially in the after-hours market. This supports the assertion of those authors who argue that after-hours markets tend to be less efficient (e.g., Barclay and Hendershott, 2003, 2004; Raudys *et al.*, 2013).

The overreaction hypothesis predicts that investors overreact by pushing asset prices too high or too low over a given period and then correcting themselves, thereby generating predictable return patterns (De Bondt and Thaler, 1985, 1987). In the case of short-term overreactions one-period price increases should be followed by price decreases on the next period and vice versa. In the case under scrutiny, the presence of price overreaction is problematic to the hypothesis of market efficiency since the size of the price reversal we detected in our sample enables the development of trading strategies capable of generating systematic abnormal profits, even after considering the typical transaction costs of ADRs. The implications of our findings to market regulators are also discussed in conclusions.

The rest of this paper is organized as follows. Section 2 reviews the related research. Section 3 describes the data and the methodologies employed in our study. Section 4 displays the empirical results. Section 5 summarizes our research and offers concluding remarks.

2. RELATED RESEARCH

Our study contributes to the literature on price efficiency of ADRs. Rosenthal (1983) performed the first test of efficiency in this market. He examined 54 ADRs from 8 countries and found evidence of weak form efficiency in weekly returns. Webster (1998) studied the market efficiency of three ADRs showing that the market prices readily reflected the information over the daily horizon. However, more recent studies present results that are at odds with market efficiency. For example, Benou (2003) documents that ADRs that experienced a price decline of more than 15% in a given month underreact to information over

the long run (up to three years), which causes prices to move in the direction of the initial price change. [Urrutia and Vu \(2006\)](#) reject the hypothesis that ADR returns follow a random walk. They conclude that the ADRs return data exhibit nonlinearity and show evidence of chaotic behavior, unlike the returns of US stocks. In a similar comparison, [Visaltanachoti and Yang \(2010\)](#) report that non-US stocks listed on the NYSE took three to four times longer to converge to market efficiency than comparable US stocks. The results presented by [Urrutia and Vu \(2006\)](#) and [Visaltanachoti and Yang \(2010\)](#) may be explained by the findings of [Demirer et al. \(2014\)](#), according to which investors in some sector-based ADR portfolios tend to herd, especially during large market downturns. Further, [Suh \(2003\)](#) shows that ADR returns are significantly influenced by US market sentiment. Finally, [Bouges et al. \(2009\)](#) and [Lobão \(2019\)](#) report the existence of significant turn-of-the-month and pre-holiday effects in ADRs, which challenges the notion that this market is efficient in the weak form.

Our paper also relates to the literature that examines the short-term predictability of international stock prices after a large daily price movement. For example, [Hamelink \(2003\)](#) studies the reaction of French stocks after a change in daily prices of at least 2.5%, 5% and 10%. He did not find any clear pattern and the trading returns seem to be too low to enable a profitable strategy. [Otcchere and Chan \(2003\)](#) show that stocks listed in Hong Kong tend to overreact after a large price shock. The same pattern of overreaction and reversal was found by [Diacogiannis et al. \(2005\)](#) in a sample of Greek stocks and by [Pham et al. \(2007\)](#) in a sample that includes Australian, Japanese and Vietnamese stocks. [Lobe and Rieks \(2011\)](#) report that the reaction to large price changes in German stocks is asymmetric in its intensity. Stocks tend to overreact showing a positive (negative) reaction after large price drops (rises), but reversals tend to be weaker after large price increases. Evidence from the UK is mixed since [Amini et al. \(2010\)](#) report reversals after large price moves whereas [Mazouz et al. \(2012\)](#) conclude that there is a pattern of price continuation but only for stocks with high liquidity risk. [Patel and Michayluk \(2016\)](#) analyse return predictability in Australian stocks, concluding that large price changes caused by liquidity trading tend to be reversed. Overall, most studies report reversals in international stock prices after large price movements and explain this by overreaction.

Finally, the present research also contributes to the literature that addresses stock pricing during after-hours. Because of technological improvements, ADRs and stocks can be traded during after-hours, that is, outside the regular trading hours. However, as argued by [Richie and Madura \(2015\)](#), the fragmentation of overnight markets raises concerns about their informational efficiency. For example, [Neumark et al. \(1991\)](#) conclude that, although after-hours pricing in foreign equity markets appeared to be efficient in processing information in the weeks immediately following the October 1987 crash, they seemed to be relatively uninformative in the following months. [Barclay and Hendershott \(2003, 2004\)](#) report large differences in the amount of both informed trading and uninformed trading after-hours. Prices are more efficient and more information is revealed per hour during the trading day than after-hours. These results suggest that information may accumulate overnight when the trading is more costly and less frequent, making prices to exhibit larger bid-ask spreads and more frequent price reversals. [Jiang et al. \(2012\)](#) conclude that after-hours trading following earnings announcements are mainly carried out by informed traders but [Li \(2016\)](#) shows that prices adjust slowly to those public announcements. [Chen et al. \(2012\)](#) find that investors trade for non-information reasons in the post-close period and trade for information reasons in the pre-open period. Short-sellers may play a relevant role

on this pricing pattern. In fact, [Alldredge et al. \(2012\)](#) conclude that the short-term trading strategies and informativeness of short-sellers are driven primarily by trading during regular market hours. In addition, [Jain et al. \(2019\)](#) show that the short-sellers' after-hour trading following quarterly earnings announcements are informed. Finally, [Raudys et al. \(2013\)](#) and [Lou et al. \(2019\)](#) argue that during the after-hours period the market is thinly traded and prices are inefficient. Price spikes up or down can be observed overnight in a pattern that can be exploited by a simple contrarian strategy. Overall, the results of this strand of the literature suggest that, relative to normal hours, price discovery after-hours is less efficient.

3. DATA AND METHODOLOGY

Nineteen years of daily opening and closing prices are used for 127 ADRs from 31 different countries spanning between January 2001 and December 2019. The 127 ADRs are traded in NYSE (19) and NYSE (116) and were issued by firms from developed markets (59) and emerging markets (68). A high proportion of the ADRs were issued by British firms (17% of the total) and Brazilian firms (11%). About half of the ADRs belong to the services sector and the manufacturing and technology sectors represent about 40% and 10% of the sample, respectively.

Normal hours returns are estimated as the log difference between the closing and opening prices on day t . After-hours returns are computed as the log difference between the opening price on day t and the closing price on day $t-1$. Normal hours period and after-hours period together cover a total of twenty-four hours. Following the literature on the topic of short-term overreaction in stock prices (e.g., [Mazouz et al., 2012](#)), we consider as potential events of overreaction the observations where the absolute returns exceeded in five, six or seven percentage points the mean return observed in the 250 days preceding the event. The period of 250 days is approximately the number of business days of a calendar year.

[Table no. 1](#) shows the number of events that satisfy the 5% trigger level, which includes extreme price increases (winners) and extreme price decreases (losers), across normal and after-hours periods by different types of ADRs.

Table no. 1 – Distribution of events (winners and losers) across normal hours and after hours that satisfy the 5% trigger level

	Winners				Losers				Total	
	Normal hours		After-hours		Normal hours		After-hours			
Service	359	26%	318	23%	309	22%	396	29%	1,382	100%
Manufacturing	390	35%	196	18%	341	31%	184	17%	1,111	100%
Technology	153	37%	66	16%	100	24%	99	24%	418	100%
Entire sample	902	31%	580	20%	750	26%	679	23%	2,911	100%

The entire sample consists of 2,911 extreme ADR price movements that meet the minimum 5% trigger level. There is a higher number of observations during daytime versus overnight both in the winners and in the losers subsamples. Most of extreme price movements are concentrated on the service ADRs, followed closely by manufacturing ADRs.

[Table no. 2](#) shows the number of subsamples across types of ADRs.

Table no. 2 – Distribution of events (winners and losers) across types of ADR that satisfy the 5% trigger level

	Total normal hours		Total after-hours		Total winners		Total losers	
Service	668	40%	714	57%	677	46%	705	49%
Manufacturing	731	44%	380	30%	586	40%	525	37%
Technology	253	15%	165	13%	219	15%	199	14%
Entire sample	1,652	100%	1,259	100%	1,482	100%	1,429	100%

The number of winners is slightly higher than the number of losers and a total of 1,652 observations qualify during daytime versus 1,259 overnight. In ADRs belonging to the manufacturing and services industries, the number of winners is higher than the number of losers. Table no. 2 shows that the specific proportion of normal hours observations versus after-hours varies by ADR type. The daytime observations dominate for manufacturing ADRs and technology ADRs but in service ADRs the number of overnight observations is higher.

Following S. J. Brown and Warner (1980), we use a mean-adjusted returns model and a time-series standard deviation to analyze the existence of overreaction taking place after a large price movement. Expected returns are calculated using a 250-day estimation period ending fifteen days before the extreme price movement.

In our empirical study, the time horizon used to test for a reversal is either the after-hours period subsequent to an extreme price movement observed during the previous normal trading period, or the normal hours period following an extreme price movement observed during the previous after-hours period.

We conduct a multivariate analysis to understand which factors may explain the existence of overreaction following extreme price movements. We considered the abnormal returns in reaction to extreme price movements to depend on the following factors: 1) the period under analysis (normal hours versus after-hours), 2) the size of the extreme return (trigger) of the ADR, 3) the volatility of the ADR, 4) the existence of tax effects, 5) the prevailing trend (bullish versus bearish) in the stock market, 6) the sector to which the firm that issued the ADR belongs, 7) the level of development of the home market (developed versus emerging market), and 8) the occurrence of the extreme return during the global financial crisis of 2007-2009.

An extreme price movement is classified according to whether it took place in daytime or overnight with a dummy variable. One should expect a larger overreaction overnight since the literature suggest that prices on this period are less efficient (e.g., Barclay and Hendershott, 2004; Raudys *et al.*, 2013).

The trigger is the return that allowed the ADR to qualify for the sample based on the +5% or -5% threshold level. One expects that a more extreme price movement may mean a greater overreaction, and thus leading to a larger correction.

ADR volatility is captured by the standard deviation of the returns in the ninety days that preceded the extreme price movement. K. C. Brown *et al.* (1993) found a positive correlation between abnormal post extreme price movement returns and changes in the volatility of returns in their sample.

Tax reasons can partially explain the reaction to an extreme return. Thus, a dummy variable is used to scrutinize whether extreme price movements occurred in December or January.

We recur to the method suggested by Pagan and Sossounov (2003) to determine the prevailing trend (bullish versus bearish) in the market of ADRs, represented by the BNY

Mellon ADR index. [Stambaugh et al. \(2012\)](#) show that prices are more prone to temporary mispricing when the market sentiment is more optimistic. Further, [Suh \(2003\)](#) found that the performance of ADRs is significantly influenced by US market sentiment.

Each ADR is classified as service, manufacturing and technology according to the sector of the issuing firm. The three types are separately coded using dummy variables representing services ADRs and technology ADRs. It is reasonable to believe that different ADR types may respond differently to pricing factors.

We also consider the influence of the country (developed or emerging) of the ADR as this factor can influence the pattern of price reversal. It is expected that ADRs from developed markets will tend to exhibit more efficient prices ([Benou, 2003](#)).

During a severe financial crisis, it is expected that the market will be less efficient and more likely to react to overreact ([Michayluk and Neuhauser, 2006](#)). Our sample period encompasses the global financial crisis of 2007-2009. We follow [Davis et al. \(2009\)](#) to define the period of crisis from October 9, 2007 to March 9, 2009.

We use the following cross-sectional model to test for the significance of the trading period (normal versus after-hours) while controlling for a group of other variables:

$$\begin{aligned} AR_i = & \beta_0 + \beta_1 AFTERHOURS_i + \beta_2 TRIGGER_i + \beta_3 VOLATILITY_i + \beta_4 TAX_i \\ & + \beta_5 TREND_i + \beta_6 SERVICES_i + \beta_7 TECH_i + \beta_8 DEVELOPED_i \\ & + \beta_9 CRISIS_i + \varepsilon_i \end{aligned}$$

where:

AR_i = absolute value of the abnormal return during the period following the extreme return,
 $AFTERHOURS_i$ = a dummy variable, which takes the value 1 if the return happens after-hours and 0 otherwise,

$TRIGGER_i$ = return of the ADR (must be $>+5\%$ or $<-5\%$),

$VOLATILITY_i$ = the standard deviation of returns observed over the ninety days that preceded the extreme return,

TAX_i = a dummy variable, which takes the value 1 if the extreme return happens during December or January and 0 otherwise,

$TREND_i$ = a dummy variable, which takes the value 1 if the stock market is in a bullish trend when the extreme price movement happens and 0 otherwise,

$SERVICES_i$ = a dummy variable, which takes the value 1 if the ADR represents the ownership of securities issued by a firm that belongs to the services sector and 0 otherwise,

$TECH_i$ = a dummy variable, which takes the value 1 if the ADR represents the ownership of securities issued by a firm that belongs to the technology sector and 0 otherwise,

$DEVELOPED_i$ = a dummy variable, which takes the value 1 if the ADR represents the ownership of securities issued by a firm that is listed in a developed market and 0 otherwise,

$CRISIS_i$ = a dummy variable, which takes the value 1 if the extreme return happens during the global financial crisis, that is, from October 9, 2007 to March 9, 2009, and 0 otherwise.

The model is tested and corrected for heteroskedasticity using White's test.

4. EMPIRICAL RESULTS

4.1 Abnormal returns following the extreme price movements of ADRs

Table no. 3 shows the abnormal returns following after-hours triggers that took place for the entire sample of winners and losers in the different subsamples. For the winners and losers, the results are shown for trigger levels of at least 5%, at least 6%, and at least 7%.

As shown in Table no. 3, the overnight winners experience an important reversal in normal hours, which is statistically significant at the conventional levels of significance when the extreme price movement is higher than 6%. In these conditions, about two thirds of the after-hour winners are followed by a reversal and the size of the reversal varies between 16.43% and 19.05% of the extreme return. The correction happening daytime indicates that the extreme returns that occurred after-hours reflect an overreaction. This is confirmed by the fact that returns are significantly negative in the following after-hours session.

Table no. 3 – Full Sample Abnormal Returns Following After-Hours Triggers

	After Hours (Period 0)	Day (Period 1)	After Hours (Period 2)	24 Hours (Periods 1-2)	Proportion of the Overreaction reversed in the following period (Pd 1AR/Pd 0 AR)
Winners					
Trigger >5% (N=580)	7.64% (36.98) *** <i>100%:0%</i>	-1.37% (-0.94) <i>36%:64%</i>	-0.03% (-0.60) <i>53%:47%</i>	-1.40% (-0.34) <i>37%:63%</i>	17.94%
Trigger >6% (N=315)	9.42% (23.76) *** <i>100%:0%</i>	-1.79% (-9.99) *** <i>34%:66%</i>	-0.30% (-4.63) *** <i>53%:47%</i>	-2.09% (-5.32) *** <i>35%:65%</i>	19.05%
Trigger >7% (N=193)	11.28% (12.80) *** <i>100%:0%</i>	-1.85% (-12.46) *** <i>35%:65%</i>	-0.44% (-5.47) *** <i>51%:49%</i>	-2.29% (-7.23) *** <i>34%:66%</i>	16.43%
Losers					
Trigger <-5% (N=679)	-7.62% (-24.21) *** <i>0%:100%</i>	2.06% (17.19) *** <i>66%:34%</i>	-0.24% (0.43) <i>46%:54%</i>	1.82% (16.07) *** <i>64%:36%</i>	27.01%
Trigger <-6% (N=397)	-9.24% (-31.96) *** <i>0%:100%</i>	2.59% (14.57) *** <i>66%:34%</i>	-0.27% (6.26) *** <i>47%:53%</i>	2.32% (8.49) *** <i>65%:35%</i>	27.98%
Trigger <-7% (N=253)	-10.85% (-13.00) *** <i>0%:100%</i>	2.89% (14.72) *** <i>65%:35%</i>	-0.24% (2.00) ** <i>49%:51%</i>	2.66% (12.60) *** <i>64%:36%</i>	26.69%

Notes: proportion of positive observations vs proportion of negative observations shown in italics.

*Values of t-statistics in parentheses. *, **, *** stand for significance levels of 10%, 5% and 1%, respectively using a 2 tailed test for significance.*

When the extreme return is negative, the reversal is even stronger, on average, although it occurs with approximately the same frequency. In this case, more than 25% of the extreme price movement that occurred in the after-hours period is reversed in the following period. However, the reversal does not continue in the following after-hours session. Overall, we can conclude that a significant response follows an extreme price movement occurred after-hours,

especially in the case of after-hours losers. This suggests that some investors that trade in normal hours capitalize on the overreaction that occurred overnight.

Table no. 4 shows the abnormal returns following extreme price changes of ADRs that occurred during normal hours for the overall sample of winners and losers and the different subsamples.

Table no. 4 – Full Sample Abnormal Returns Following Day Triggers

	Day (Period 0)	After Hours (Period 1)	Day (Period 2)	24 Hours (Periods 1-2)	Proportion of the Overreaction reversed in the following period (Pd 1AR/Pd 0 AR)
Winners					
Trigger > 5% (N=902)	7.37% (33.87)*** <i>100%:0%</i>	-0.41% (-1.94)* <i>48%:52%</i>	0.12% (1.25) <i>47%:53%</i>	-0.29% (-3.19)*** <i>52%:48%</i>	5.61%
Trigger > 6% (N=517)	8.80% (45.03)*** <i>100%:0%</i>	-0.49% (-2.57)** <i>47%:53%</i>	-0.05% (10.88)*** <i>45%:55%</i>	-0.54% (-13.45)*** <i>42%:58%</i>	5.52%
Trigger > 7% (N=331)	10.13% (12.32)*** <i>100%:0%</i>	-0.67% (-1.77)* <i>42%:58%</i>	-0.09% (-0.07) <i>44%:56%</i>	-0.75% (-1.70)** <i>38%:62%</i>	6.58%
Losers					
Trigger < -5% (N=750)	-7.11% (-22.91)*** <i>0%:100%</i>	0.59% (3.23)*** <i>59%:41%</i>	0.25% (-1.52) <i>56%:44%</i>	0.84% (4.75)*** <i>60%:40%</i>	8.31%
Trigger < -6% (N=419)	-8.46% (-15.88)*** <i>0%:100%</i>	0.61% (2.88)*** <i>57%:43%</i>	0.21% (-4.46)*** <i>56%:44%</i>	0.82% (7.34)*** <i>59%:41%</i>	7.21%
Trigger < -7% (N=254)	-9.76% (-24.40)*** <i>0%:100%</i>	0.69% (3.16)*** <i>56%:44%</i>	0.23% (-1.00) <i>54%:46%</i>	0.91% (3.79)*** <i>60%:40%</i>	7.03%

*Note: proportion of positive observations vs proportion of negative observations shown in italics.
Values of t-statistics in parentheses. *, **, *** stand for significance levels of 10%, 5% and 1%,
respectively using a 2 tailed test for significance.*

The results reveal important differences in comparison with the case where the extreme returns occurred during the after-hours period. The reversals observed in reaction to extreme price movements that occurred during normal hours appear to be substantially less pronounced, with a size that is about one third of the reversals presented in Table no. 3. In spite of that, the reversals are statistically significant at the conventional significance levels. The frequency of the corrections is also slightly lower, not even reaching 60% of the sessions, regardless of the trigger level. As in the previous case, the reversals observed following a negative shock appear to be more pronounced.

Table no. 5 compares the magnitude of reversal and continuation between the normal hours and after-hours periods.

Table no. 5 – Comparison of abnormal returns between normal hours and after-hours periods

Trigger	Abnormal returns following Day Trigger	Abnormal returns following After-hours Trigger	Mean Difference	T-stat.
Winners				
5%	-0.41%	-1.37%	0.96%	-0.87
6%	-0.49%	-1.79%	1.31%	2.06**
7%	-0.67%	-1.85%	1.19%	3.39***
Losers				
5%	0.59%	2.06%	-1.47%	-6.46***
6%	0.61%	2.59%	-1.98%	-5.56***
7%	0.69%	2.89%	-2.21%	-6.27***

Note: *, **, *** stand for significance levels of 10%, 5% and 1%, respectively using a 2 tailed test for significance.

The table shows that the mean difference between the abnormal returns following normal hours and after-hours periods is only statistically different from zero when the extreme returns qualify for the 6% and 7% triggers levels. The mean difference in the reversal reaches a higher level (1.31%) following an extreme shock of at least 6%.

As observed before, the reversal tends to be more pronounced following extreme negative shocks happening overnight. For daytime losers that satisfy the 5% trigger level, the reversal occurring overnight is 0.59% while for overnight losers, there is a correction in the following period of 2.06% on average. The mean difference between the two responses is -1.47%, which is statistically different from zero at the 1% level. The results are analogously significant for the 6% and 7% trigger levels.

Overall, the observed returns indicate that there was a significant difference in the response in the two trading periods, especially regarding extreme negative returns.

4.2 Multivariate analysis of ADR winners and losers

Results of the multivariate analysis of ADR winners and losers are shown in Table no. 6. For winner ADRs, the AFTERHOURS dummy variable is significantly positive at the 1% level, indicating that the reversal following an overnight winner is more significant than the reversal following a daytime winner.

Table no. 6 – Cross-sectional Regression of AR following extreme price movements for full sample of ADRs

Sample	INTER-CEPT	AFTER-HOURS	TRIGGER	VOLATILITY	TAX	TREND	SERVICES	TECH	DEVELOPED	CRISIS	Adj-R2
Winners (N=1,482)	0.001 (0.770)	0.009*** (0.000)	-0.015 (0.716)	-0.018 (0.847)	-0.004 (0.135)	-0.002 (0.299)	-0.001 (0.515)	0.001 (0.710)	-0.002 (0.231)	-0.002 (0.358)	0.012
Losers (N=1,429)	-0.009* (0.055)	0.015*** (0.000)	-0.105* (0.058)	0.284*** (0.001)	0.001 (0.702)	0.000 (0.899)	-0.001 (0.678)	-0.007*** (0.007)	0.002 (0.256)	0.001 (0.816)	0.072

Note: The absolute value of the abnormal return following one extreme price movement of at least 5% is the dependent variable.

AFTERHOURS is a dummy variable that takes the value 1 when the extreme price movement happened after-hours and 0 otherwise. TRIGGER is the size of the extreme return. VOLATILITY is the value of the standard deviation of returns in the ninety days that preceded the extreme return. TAX is a dummy variable that takes the value 1 when the extreme return occurred in December or January and 0 otherwise. TREND is a dummy variable that takes the value 1 when the extreme return happened during a bullish market and 0 otherwise. SERVICES and TECHNO are dummy variables that take the value 1 when the extreme returns pertain, respectively, to a service ADR or to a technology ADR, respectively and 0 otherwise. DEVELOPED is a dummy variable that takes the value 1 if the underlying stocks are listed in a developed market and 0 otherwise. CRISIS takes the value 1 if the extreme return occurred during the global financial crisis, that is, from October 9, 2007 to March 9, 2009 and 0 otherwise.

Robust p-values in parentheses. *, **, *** stand for significance levels of 10%, 5% and 1%, respectively.

This result is consistent with the earlier finding in the univariate analysis that on average reversals among winners are larger following extreme price increases observed during after-hours periods. None of the remaining independent variables is statistically different from zero.

A similar multivariate model was used to assess the entire sample of losers. The AFTERHOURS dummy variable is again significantly positive at the 1% level, which suggests that the reversal following an overnight loser is more pronounced than the reversal following a daytime loser. This finding also confirms our earlier results. The TRIGGER variable is negative and significant at the 10% level, indicating that there is a weak negative relationship between the size of the extreme price movement and the subsequent reversal. The VOLATILITY variable is positive and significant at the 1% level, which suggests that the reversal tends to be more pronounced when the volatility is higher. The TECH dummy variable is significantly negative at the 1% level, which means that the reversals of the ADRs that belong to the technology sector were less pronounced.

5. CONCLUSIONS

ADRs are one of the most important instruments available to US investors for diversifying their investments internationally. In spite of their economic importance there are no studies on the short-term predictability of these securities following extreme price shocks. Our paper fills this gap by examining the short-term predictability of ADRs in reaction to extreme price movements that occurred within either normal trading hours or after-hours. We used an extensive sample covering nineteen years of daily opening and closing prices for 127 ADRs from 31 different countries. We show that the extreme returns represent on average an overreaction, leading to a significant reversal in the following period. This evidence is difficult to reconcile with the notion that ADR returns are not predictable, thus challenging the weak version of the market efficiency hypothesis. Our results are consistent with the literature that reports reversals in international stock prices after large price movements (e.g., [Diacogiannis et al., 2005](#); [Amini et al., 2010](#)). In our sample, the price reversal tends to be much more pronounced when the extreme price movements take place after-hours. This finding supports the assertion that price discovery during overnight tends to be less efficient (e.g., [Barclay and Hendershott, 2003, 2004](#); [Raudys et al., 2013](#)).

Our study brings important implications for both regulators and market practitioners. Concerning regulation, our results recommend market regulators to focus their resources on supervising the ADR pricing that takes place after-hours. The existence of overreaction in prices means that some investors are trading excessively and in consequence they are bearing unnecessary trading costs. Second, for market practitioners, our evidence on price predictability suggests the existence of profitable market opportunities. For example, during the sample period, for after-hours losers satisfying the 7% minimum trigger, the mean reversal in the following period is 2.89%, while for after-hours winners, there is a correction of -1.85% on average. [Braga-Alves \(2018\)](#) estimates that the ADR trading costs, including the effective spread and the price impact of investing, amount on average to 31 basis points. Therefore, our results imply that a contrarian strategy conducted by an execution-savvy short-term investor can profit from the pattern of overreaction and reversal in ADRs.

Further avenues of research regarding the patterns of short-term predictability in the market of ADRs may include studying the role played by different classes of investors such

as short-sellers and institutional investors on price overreaction; and considering the possibility that the results presented in this study may interact with other patterns of predictability exhibited by ADR prices.

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