Short-term predictability of stock market indexes following large drawdowns and drawups

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Abstract

The Efficient Market Hypothesis is one of the most popular subjects in the empirical finance literature. Previous studies in the stock markets, which are mostly based on fixed time price variations, do not provide conclusive findings, in which evidence of short-term predictability varies according to different samples and methodologies. In this work, we propose a novel approach and use drawdowns and drawups as triggers in order to investigate the existence of short-term abnormal returns in the stock markets. As these measures are not computed within a fixed time horizon, they are flexible enough to capture time-dependent subordinated processes that could be driving market under or overreaction. According to our results the Efficient Market Hypothesis is supported by the majority of estimates. Results also provide stronger support for underreation hypothesis than overreaction, with the highest prevalence of return continuations than reversals. Evidence for UIH is present in some markets, mainly after events of lower magnitude.

Keywords: Market efficiency, Abnormal returns, Drawdowns

JEL Classification: G1, G14, G15

1 Introduction

In 2008, when Queen Elizabeth II asked a group of professors at the London School of Economics why had nobody noticed the financial crisis coming[2], your highness was probably not aware she was addressing one of the most important and controversial topics in Finance: the predictability of the financial markets. The origin of this debate dates back at least to Bachelier (1900), which developed the mathematics of the Brownian motion as a model for stock prices' variations and concluded that they followed a random walk, in which expected speculators' profits should be zero. Since then, the randomness of the financial markets became a subject of great interest and scrutiny among academics and market participants.

Almost half a century ago, Prof. Eugene F. Fama published his first broad review of the theoretical and empirical literature on this subject[3] and, at that time, he already recognized the area was "so bountiful" that he apologized for any missing references. His paper consolidated and popularized the concept of efficient market as one "in which prices allways fully reflect available information" and defined the classic taxonomy that distinguishes the three different forms of market efficiency: weak (past return), the semi-strong (public information) and the strong (public and private information), according to the type of information used to predict future prices.

[1] The views expressed in this paper are those of the author and do not necessarily reflect those of the Banco Central do Brasil.

[2] Why did nobody notice it?, Zingales (2012).

[3] Fama (1970).

After that, the academic debate has been driven around what is now well known as the "Efficient Market Hypotheis" (EMH), which evolved from the random walk theory of asset prices[4]. As Ball (2009) have explained, the idea behind the Hypothesis merges the insight that competition among rational agents reduces trading margins close to zero with another one stating that asset prices fluctuations are driven solely by the arrival of new and relevant information. Rational expectation plays a central role explaining how transaction prices remain as best estimates for market equilibrium. When all investors are rational, no one would be willing to enter into a mispriced transaction. Even with the presence of some irrational agents, the competition among rational arbitrageurs would avoid prices to move away from market equilibrium (Friedman, 1953).

As emphasized later by Fama (1991) in his second literature review on the issue, this hypothesis cannot be tested empirically without a complementary assumption about an equilibrium model that would properly reflect all available information into the process of price discovery. The joint-hypothesis problem, as he calls it, does not make empirical research uninteresting at all. Despite not being able to test market efficiency alone, he argues that the field has developed as one of the most successful in empirical economics improving our understanding on the behavior of securities returns.

With the development of the field of cognitive and social psychology[5], economists were provided with a better understanding of how biases on judgments and beliefs can affect the individual decision-making process as well as the market behavior as a whole. The emergence of "Behavioral Economics", though, added many insights to the market efficiency debate by incorporating new evidence on human behavior departures from rationality hypothesis. Inspired by the evidence on Kahneman and Tversky (1979) that individuals tend to underweight base rate (prior) data and overweight recent information, DeBondt and Thaler (1985) presented their widely known early research finding empirical evidence of long-term overreaction in the US stock market.

The first studies on short-term overreaction, however, showed quite controversial results. While Arbel and Jaggi (1982) and Atkins and Dyl (1990) found no evidence on the violation of the EMH, Bremer and Sweeney (1991) found that large negative daily returns are followed, on average, by significant abnormal positive returns. Overall, the literature presents different theories to explain price behavior following large price variation events and there seems to be no consensus on which of them prevails. Besides overreaction, another behavioral explanation, known as the underreaction hypothesis[6], assumes that new information is not immediately incorporated into market prices causing near term future returns to follow the direction of preceding large price changes.

It is also possible that abnormal returns may be explained by no anomaly at all, based on conventional rational expectations' framework. Under the Uncertain Information Hypothesis (UIH)[7], the systematic risk of stocks tend to increase at the same time of large price variations, which leads to a demand for higher expected returns from risk-averse rational investors. As a result, this hypothesis predicts return continuation after large price rises and reversals after large drops. In addition, there are also explanations related to market microstructure, in which spurious serial correlation may be caused by unsynchronized trading or bid-ask bounce effects[8].

Amini et al. (2013) offer a broad and detailed review on the short-term predictability of stock markets after the observation of large price variations, comparing different markets, time periods and methodologies used in the empirical research. In their conclusions, they suggest that the literature could benefit from future research using different ways to define large returns, such as looking at those conditional on other factors.

[4]Fama (1965) and Samuelson (1965).

[5]See Kahneman and Tversky (1982) for an earlier reference.

[6]Benou (2003).

[7]Brown et al. (1988).

[8]Cox and Peterson (1994).

In this work, we try to follow that idea and propose to use drawdowns and drawups as triggers in order to investigate the existence of short-term abnormal returns in the stock markets, using 10 different stock price indexes from developed and emerging markets. Drawdowns and drawups are defined as the cumulative price variation on a sequence of negative or positive returns, respectively. Different from fixed time measures as daily, weekly or monthly returns, the duration of drawdowns and drawups varies randomly according to investors' behavior. As these measures are not computed within a fixed time horizon, they are flexible to capture time-dependent subordinated processes (local dependence) that could be driving investors' under or overreaction [9]. Therefore, the use of drawdowns and drawups may provide additional understanding of market behavior compared to fixed time statistics, specially those related to the occurrence of large returns[10].

We estimate the abnormal returns following the dummy variable approach similar to Karafiath (1988) and Mazouz et al. (2009) for time periods from 1 to 21 business days after the event ending dates. Residual variance is assumed to follow the GJR-GARCH model proposed by Glosten et al. (1993), which captures both GARCH structure and the asymmetries in the data and, therefore circumvents some restrictive assumptions on standard OLS estimation. As pointed out by Mazouz et al. (2009), GARCH methods lead to higher estimation efficiency, avoiding invalid inferences due to failures in capturing market uncertainty variations close to event periods.

Our results show a great variety of estimates across the different stock market indexes in the sample, providing evidence that price behavior after large drawdowns and drawups varies according to country specific market features. Similarly to previous empirical literature, we do not provide conclusive evidence on short-term predictability of stock market returns following large price variations. The Efficient Market Hypothesis is supported by the majority of estimates. Results also providence stronger support for underreation hypothesis than overreaction, with the highest prevalence of return continuations than reversals. Evidence for UIH is present is some markets, mainly after events of lower magnitude.

The remainder of the paper proceeds as follows. The next section presents the data and Section 3 discusses the methodology. Section 4 describes the empirical results, while the conclusion is presented in the last section.

2 Data Sample

Data used in this research is composed by daily close prices of 10 stock price indexes within 8 different countries: the Dow Jones Industrial Average - DJIA (US); the S&P500 (US); the Nasdaq Composite - NASDAQ (US); The Euro Stoxx 50 Index - SX5E (European Union); the London stock exchange - FTSE 100 (UK); the Hong Kong stock exchange, Hang Seng - HSI (Hong Kong); the Brazilian stock exchange index - IBOVESPA (Brazil); Mexican stock exchange - MEXBOL (Mexico); Indonesian stock exchange - JCI (Indonesia); and the Korean stock exchange - KOSPI 200. We intentionally selected data from developed and emerging economies to compare their results and to try to provide anecdotal evidence on eventual differences between these 2 groups.

Daily returns are obtained by the natural logarithm of the ratio between the close price of each business day and the close price of the previous business day (and they are multiplied by 100 to express percentage returns). Observation periods are different among indexes but all series ends at December 31, 2015. The

[9]As emphasized by Mandelbrot (1963), for price returns distributions with infinite second moment, the total price variation is usually concentrated in a few trading days. According to Clark. (1973), these turbulent cascades could be explained by some time dependent subordinated process, that could be related to market microstructure variables, such as trading volume or number of trades, which are ultimately related to investors' behavior. Dacorogna et al. (1996), Levitt (1998), Weron and Weron (2000) and Gerhard and Hautsch (2002) are examples of alternative ways to capture the dynamics of the financial time series using the concept of elastic time.

[10]Mandelbrot (1972), Johansen and Sornette (2001) and Mendes and Brandi (2004).

DJIA is longest series in the sample, with 28,885 daily returns (around 116 years) and the IBOVESPA is the shortest, with 5,309 daily returns (around 22 years). Table 1 presents basic statistics of the daily returns of all indexes. Most of the results are consistent with previously documented stylized facts of stock market returns, such as negative skewness and excess kurtosis[11]. Differences in the number of drawdowns and drawups are explained by our strict definition, in which consecutive days with same price causes the ending of such events.

Table 1: Basic statistics of stock market indexes' daily returns (in percentage points).

	Index	N	Init	Mean	Median	Min	Max	Std.Dev.	Skew	Kurtosis
1	DJIA	28885	1900-06-27	0.03	0.05	-22.61	15.34	1.13	-0.42	21.11
2	SP500	21972	1928-01-03	0.03	0.05	-20.47	16.61	1.18	-0.08	17.36
3	NASDAQ	11194	1971-02-08	0.04	0.11	-11.35	14.17	1.24	-0.07	10.08
4	SX5E	7341	1987-01-01	0.03	0.05	-7.93	11.00	1.32	0.01	6.02
5	FTSE100	7969	1984-01-04	0.03	0.06	-12.22	9.84	1.10	-0.31	8.94
6	HSI	11289	1964-08-31	0.07	0.06	-33.33	19.79	1.90	-0.16	20.14
7	IBOVESPA	5309	1994-01-03	0.12	0.11	-15.82	33.41	2.32	0.99	15.34
8	MEXBOL	5350	1994-01-20	0.07	0.07	-13.34	12.92	1.54	0.19	6.97
9	JCI	7859	1983-04-05	0.06	0.02	-20.17	49.64	1.61	4.72	139.80
10	KOSPI	9640	1980-01-05	0.04	0.02	-12.02	11.95	1.50	-0.07	5.17

2.1 The Anatomy of Drawdowns and Drawups in the Stock Markets

Drawdowns and drawups are defined as the total percentage price variation observed in a period of consecutive negative or positive returns, respectively. Formally, assume P_t as the asset price (index value) at day t and $r_t = (P_t/P_{t-1} - 1)$ as the daily return at this same date. P_t is said to be a local maximum when prices in the previous and following day are lower, $P_{t-1} < P_t > P_{t+1}$. Local minimum, reversely, are defined when $P_{t-1} > P_t < P_{t+1}$. A drawdown with duration equal to d days is defined as a sequence of price drops $P_t > P_{t+1} > ... > P_{t+d}$, where P_t is a local maximum and P_{t+d} is the following local minimum. Accordingly, drawdowns' severities may be computed in both of the following ways[12]:

$$\frac{P_{t+d}}{P_t} - 1 = \prod_{i=1}^{d} (1 + r_{t+i}) - 1 \tag{1}$$

Table 2 summarizes simple statistics of drawdowns and drawups of all indexes. In general, average returns of drawups are slightly higher than average returns of drawdowns. On average, drawdowns and drawups are hogher for emerging markets, what is consistent with the higher risk premia and volatilities observed in these higher risk environment.

For developed markets, drawdowns distributions seems to present a longer tail that drawups distributions, as we can see the three largest drawdowns showing more severity that the three largest drawups. In the case of emerging markets, it is quite the opposite, where largest drawups are observed with higher magnitudes than largest drawdowns.

2.1.1 The First Dimension - Magnitude

Drawdowns and drawups are featured by two dimensions: magnitude and duration. Tables 3 and 4 show drawdowns and drawups' frequencies according to different severities' ranges, based on multiples of the

[11] Rydberg (2000).

[12] Drawups are defined analogously, considering positive returns.

sample standard deviation of daily returns of each index. In general, the stock market indexes present similar distributions, where most of drawdowns and drawups' severities are concentrated in the 0-1σ range with relative frequencies from 55% to 60%, showing a lower number of observations for higher severity ranges. Drawups seem to be concentrated in higher severities ranges than drawdowns, as we can observe frequencies in the first range categories around 50%. The JCI Index seems to be an outlier in this dimension, showing more frequency than the other indexes in the lowest severity range both for drawdowns and drawups.

In this work, as we are concerned with the information embedded in market events with large magnitudes, we will focus in drawdowns and drawups of magnitude higher than 2 daily returns' standard deviations, which represent around 20% of drawdowns and drawups in each index sample.

Table 2: Basic statistics of drawdowns and drawups

	Index	NDD	MeanDD	Min	Min2	Min3	NDU	MeanDU	Max	Max2	Max3
1	DJIA	6947	-1.48	-30.68	-28.22	-23.62	6992	1.58	22.96	18.57	17.44
2	SP500	5185	-1.53	-28.51	-22.90	-22.74	5210	1.65	22.46	20.83	17.72
3	Nasdaq Comp.	2434	-1.75	-25.30	-24.61	-22.63	2435	1.95	16.32	14.17	13.95
4	SX5E	1827	-1.74	-19.68	-17.52	-15.89	1829	1.85	17.47	15.04	13.27
5	FTSE100	1984	-1.48	-21.73	-14.62	-13.69	1989	1.59	17.75	15.43	11.22
6	HSI	2687	-2.40	-41.69	-38.57	-32.16	2689	2.67	48.24	38.75	29.85
7	Ibovespa	1307	-2.92	-34.63	-31.18	-31.01	1307	3.36	48.93	41.80	35.05
8	MexBol	1241	-2.11	-20.75	-20.59	-18.85	1241	2.39	22.99	17.90	15.07
9	JCI	1679	-1.87	-32.09	-22.93	-22.83	1702	2.11	68.67	35.85	23.30
10	KOSPI	2237	-2.09	-25.53	-22.27	-18.67	2240	2.26	21.09	20.53	19.32

Table 3: Number of drawdowns observations by magnitude ranges.

	Index	Total	0-1σ	1-2σ	2-3σ	3-4σ	4-5σ	5-6σ	>6σ
1	DJIA	6947	4022	1524	704	310	162	82	143
2	SP500	5185	3048	1123	492	235	113	71	103
3	Nasdaq Comp.	2434	1391	498	245	120	69	40	71
4	SX5E	1827	1037	418	181	83	40	30	38
5	FTSE100	1984	1091	470	230	84	50	28	31
6	HSI	2687	1613	595	231	105	50	36	57
7	Ibovespa	1307	751	317	131	49	22	15	22
8	MexBol	1241	688	284	122	67	28	25	27
9	JCI	1679	1138	253	129	54	40	22	43
10	KOSPI	2237	1222	513	235	116	74	30	47

Table 4: Number of drawups observations by magnitude ranges.

	Index	Total	0-1σ	1-2σ	2-3σ	3-4σ	4-5σ	5-6σ	>6σ
1	DJIA	6992	3552	1873	824	393	161	83	106
2	SP500	5210	2657	1402	618	279	111	55	88
3	NASDAQ	2435	1149	629	325	143	84	41	64
4	SX5E	1829	910	517	218	86	48	21	29
5	FTSE100	1989	972	541	257	116	51	19	33
6	HSI	2689	1420	684	289	126	71	44	55
7	IBOVESPA	1307	650	349	180	61	24	14	29
8	MEXBOL	1241	617	300	149	82	39	22	32
9	JCI	1702	1021	342	151	77	44	20	47
10	KOSPI	2240	1159	532	261	114	73	31	70

2.1.2 The Second Dimension - Duration

Tables 5 and 6 present the observed frequencies os drawdowns and drawups' durations, described in business days. The longest duration of negative consecutive returns correspond to NASDAQ's 16 business days, for the developed economies, and 19 business days of JCI, for the emerging markets. On the gains side, NASDAQ presented the longest drawup duration equivalent to 19 business days. For all indexes, the distributions of drawdowns' durations seem to be more concentrated in the shortest duration, 1 business day, as the observed frequecies of drawups present higher values for longer durations than drawdowns ones. As we can see further we will provide additional analysis focusing on drawdowns and drawups with duration greater than 2 business days, trying to catch information provided by events with persistence through longer time periods. We did not find any specific pattern comparing figures from developed and emerging markets.

Table 5: Observed frequencies (%) of the duration of drawdowns in number of business days. Last column presents maximum duration of drawdons for each index.

	Index	1	2	3	4	5	6	7	8	9	≥ 10	Max
1	DJIA	49.91	25.78	13.04	5.77	2.99	1.41	0.63	0.32	0.04	0.10	12.00
2	SP500	49.43	25.67	13.64	5.82	2.99	1.39	0.58	0.25	0.12	0.12	12.00
3	NASDAQ	49.10	24.90	13.23	5.96	3.66	1.56	0.82	0.49	0.12	0.16	16.00
4	SX5E	51.01	26.44	12.59	4.87	3.07	1.15	0.38	0.22	0.16	0.11	11.00
5	FTSE100	51.36	24.45	14.26	5.65	2.62	1.06	0.45	0.05	0.05	0.05	11.00
6	HSI	48.86	25.01	13.58	6.33	3.24	1.67	0.67	0.45	0.07	0.11	11.00
7	IBOVESPA	49.89	26.93	12.55	5.51	3.14	1.22	0.38	0.23	0.15	0.00	9.00
8	MEXBOL	48.51	24.01	14.50	6.29	3.38	1.85	1.05	0.16	0.24	0.00	9.00
9	JCI	51.28	22.45	11.91	5.54	4.17	1.91	1.25	0.42	0.54	0.54	19.00
10	KOSPI	47.61	25.35	11.98	6.93	4.16	2.19	0.98	0.45	0.22	0.13	11.00

Table 6: Observed frequencies (%) of the duration of drawups in number of business days. Last column presents maximum duration of drawups for each index.

	Index	1	2	3	4	5	6	7	8	9	≥ 10	Max
1	DJIA	44.67	26.04	14.14	7.45	3.60	2.13	0.92	0.61	0.21	0.21	13.00
2	SP500	43.76	25.43	14.82	7.70	3.88	2.17	1.11	0.54	0.31	0.29	14.00
3	NASDAQ	39.26	22.75	15.65	8.83	5.13	3.08	2.05	1.48	0.53	1.23	19.00
4	SX5E	46.91	25.97	12.03	6.83	4.65	1.97	0.87	0.49	0.11	0.16	13.00
5	FTSE100	46.10	26.50	13.47	6.23	4.07	1.91	0.96	0.40	0.15	0.20	11.00
6	HSI	45.85	25.36	12.72	6.92	4.28	2.19	1.34	0.67	0.26	0.41	11.00
7	IBOVESPA	46.75	25.71	12.85	6.96	3.67	1.76	1.15	0.31	0.31	0.54	15.00
8	MEXBOL	43.59	25.06	13.62	7.33	4.75	2.82	1.53	0.73	0.32	0.24	10.00
9	JCI	44.36	24.62	11.46	7.52	4.82	2.94	1.65	0.71	0.76	1.18	17.00
10	KOSPI	46.34	24.73	12.32	7.28	4.60	1.88	1.61	0.67	0.13	0.45	13.00

2.1.3 Relationship Between Two Dimensions

It is reasonable to assume that longer drawdowns and drawups will provide returns of higher magnitudes. Among the stock market indexes in our sample, correlations between drawdowns' durations and severities lies around -0.5 to -0.7, while drawups' correlations are calculated around 0.5 to 0.7. Table 7 presents the distribution of drawdowns and drawups durations for samples with magnitudes higher than multiples of the DJIA daily returns' standard deviation. For samples with higher severities, the duration mode increases to

3 or 4 days, showing that higher severity events are associated with longer duration processes. Also, drawdowns and drawups lasting one day tend to be less frequent as magnitude rises whereas longer durations' frequencies tend to be more prevalent. This same pattern is observed for the other indexes of our dataset.

Table 7: Distribution of drawdowns' and drawups' durations for samples with magnitudes higher than multiples of daily returns' standard deviation - DJIA and IBOVESPA

DJIA Drawdowns

Index	Total	1σ	2σ	3σ	4σ	5σ	6σ
1 day	0.50	0.21	0.11	0.07	0.05	0.04	0.05
2 days	0.26	0.30	0.24	0.21	0.20	0.17	0.16
3 days	0.13	0.24	0.25	0.25	0.24	0.24	0.23
4 days	0.06	0.12	0.17	0.15	0.15	0.14	0.15
5 days	0.03	0.07	0.11	0.13	0.13	0.13	0.11
>5 days	0.03	0.06	0.11	0.18	0.23	0.28	0.29

DJIA Drawups

Index	Total	1σ	2σ	3σ	4σ	5σ	6σ
1 day	0.45	0.19	0.11	0.10	0.09	0.08	0.09
2 days	0.26	0.29	0.20	0.17	0.16	0.16	0.19
3 days	0.14	0.23	0.22	0.19	0.13	0.15	0.16
4 days	0.07	0.14	0.20	0.19	0.19	0.21	0.21
5 days	0.04	0.07	0.12	0.12	0.12	0.08	0.09
>5 days	0.04	0.08	0.16	0.23	0.31	0.31	0.25

The average daily returns of drawdowns and drawups for different durations are illustrated in Figure1. Overall, we can observe that not only drawdows' magnitudes tend to grow with duration, but also daily average severity of drawdowns increase with duration. Regarding drawups, we observe the opposite, in which daily average returns of drawups decreases with the duration. Comparing the two groups of countries, we can observe higher disparity between emerging markets and bigger variation of daily average returns for different durations. This seems to be a normal feature due to the higher volatility and fatter tails observed in emerging stock markets.

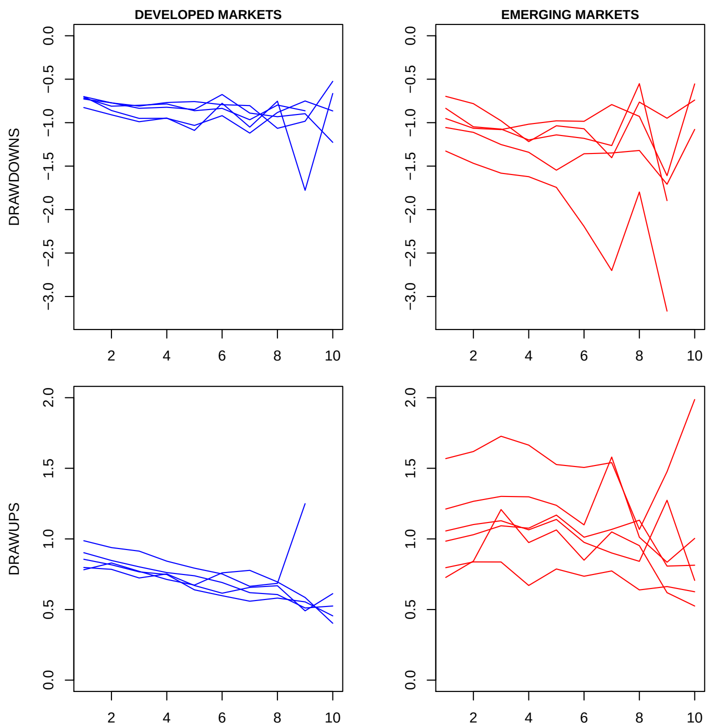
3 Methodology

Large returns are defined based on whether the magnitude of drawdowns or drawups is located in different variation ranges computed for each index separately, according to the standard deviation of its sample daily returns (σ), as shown in Table 1. For drawdowns, the ranges are defined as $-3\sigma \leq DD_{td} < -2\sigma$ and $DD_{td} < -3\sigma$. Drawdups ranges are defined similarly, as follows: $2\sigma < DU_{tu} \leq 3\sigma$ and $3\sigma < DU_{tu}$. The threshold of 2σ was defined to limit our analysis to large price variations and is consistent with previous studies related to stock market indexes[13].

As these measures are computed during different time spams, the event ending date is taken as the day of the last negative return on a drawdown (or the local minimum day) or the last positive return on a drawup (or the last local maximum day). To assess whether post-event returns can be considered abnormal, we follow the dummy variable approach in line with Karafiath (1988) and Mazouz et al. (2009). For each day t in the sample of daily returns, $D_{t,2}$ is the dummy variable that equals 1 if t is the second business date after the event ending date and 0 otherwise. Dummy variables for windows greater that 2 business days will be equal to 1 whenever any specific date belongs to a time window that ranges from the second business day immediately after the event and the specified maximum number of business days in each window. Formally, as defined in

[13] See Lasfer et al. (2003) and Nam et al. (2006) for examples.

Figure 1: Average daily returns of drawdowns and drawups by different durations. Developed markets on the left and emerging markets on the right



Mazouz et al. (2009), $D_{t,2}$, $D_{t,3}$, ..., $D_{t,N}$ will take value equal to 1 if t $\in$ [+2, +2], [+2, +3], ..., [+2, +N] and 0 otherwise, where [+2, +N] is the period span comprised by the second and the N-iest business day after the event ending date.

The presence of abnormal returns is investigated through the estimation of the following regression for each stock market index daily log return r_t:

$$logr_t = \alpha + \phi_n D_{t,n} + \epsilon_t \tag{2}$$

, where α is the constant, ϕ_n are the coefficients of the dummy variables $D_{t,n}$ and $\epsilon_t \sim N(0, h_t^2)$. To account for well documented pattern on the volatility of stock index returns[14] and to avoid estimation inefficiencies due to constant volatility assumption, the variance on eq.(2) is assumed to be conditional and to follow a GJR-GARCH model:

$$h_t^2 = \omega + (\delta + \nu \mathbb{1}_{t-1})\epsilon_{t-1}^2 + \beta h_{t-1}^2 + \gamma_n D_{t,n} \tag{3}$$

, where ω is a constant, δ and β are the conventional GARCH coefficients (Bollerslev (1986)), γ is the assymetry coefficient proposed by Glosten et al. (1993) and $\mathbb{1}_{t-1}$ is the indicator variable, which is equivalent to 1 when $\epsilon_{t-1} < 0$ and 0 otherwise. Cumulative abnormal returns associated with windows ending at the n-iest business day after events end dates are estimated as $CAR_n = \phi_n \times$ (n-1). We have excluded the first business day after events' ending dates from previous dummies' windows because, by definition, they will

[14] Black (1976), Cont (2001), Mandelbrot (1963), Clark. (1973), among others.

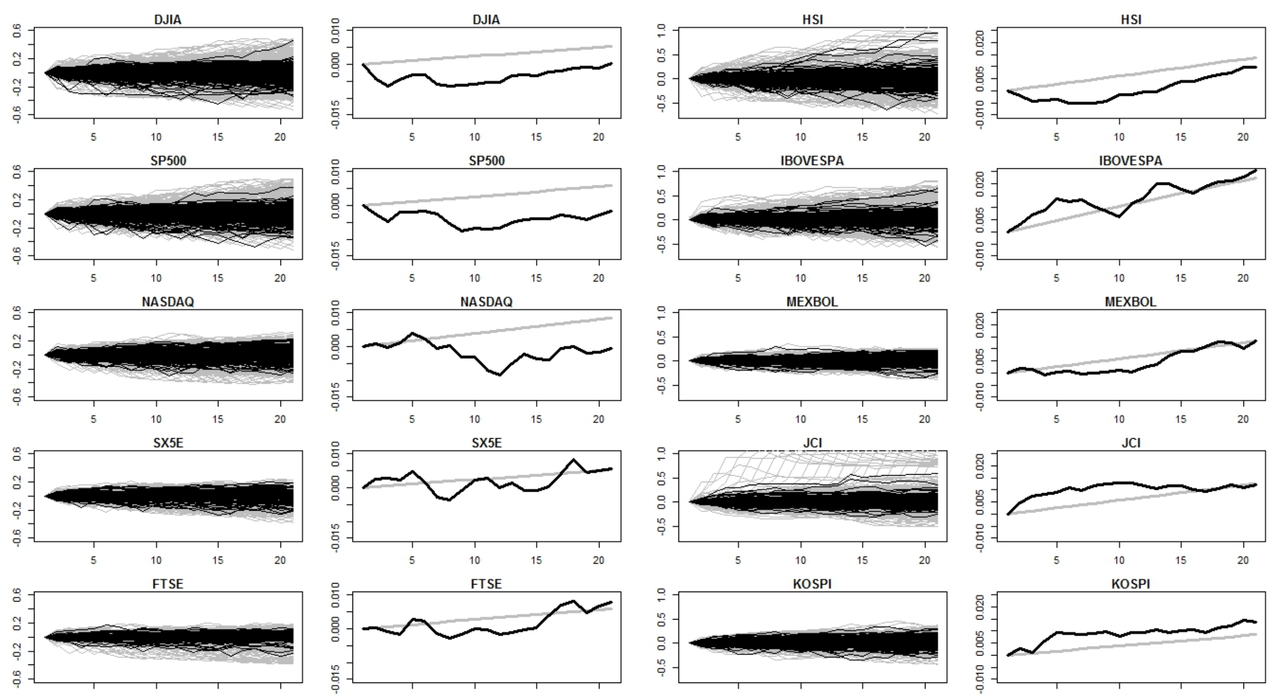
show only positive returns in the case of drawdowns and negative returns, taking drawups as the events. Also, as drawdowns and drawups are defined in a sequence of cumulative negative or positive returns, respectively, In the next section, we provide additional analysis to test for abnormal returns in at drawdowns' and drawups' ending dates.

4 Empirical Analysis

4.1 Preliminary Investigation on Returns After Drawdowns and Drawups

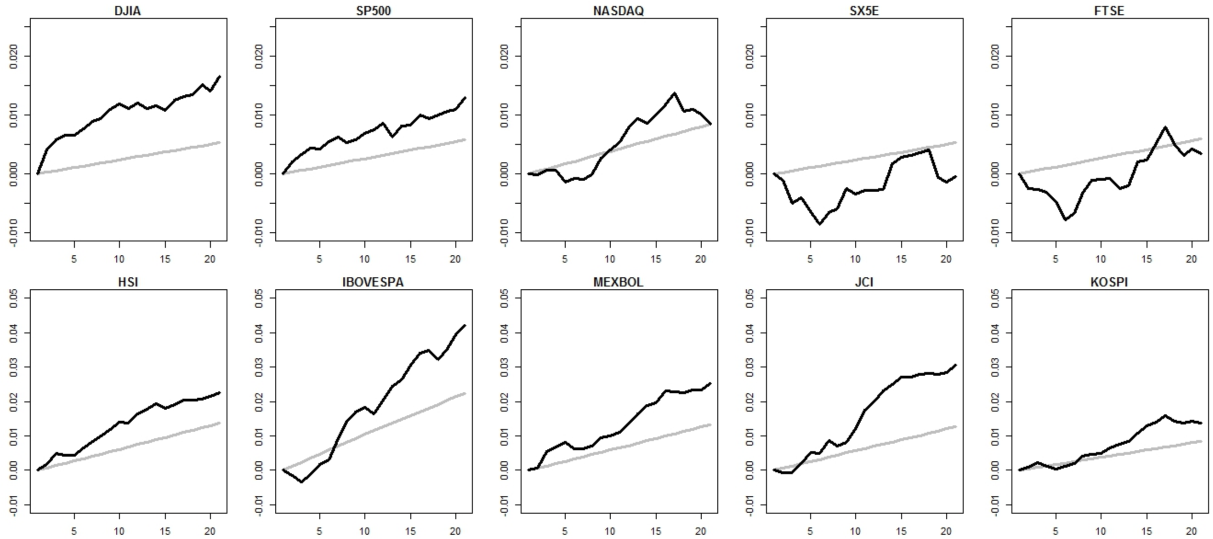
Figure 2 presents cumulative daily returns of the 63 consecutive business days after drawdowns with absolute severity equal to or higher than 3 standard deviations of sample daily returns os each stock market index. The graphs show every and average cumulative return following the second business day after drawdowns ending dates and the average figures. On the right column, we show the graphs with the average cumulative daily returns (gray line) and the cumulative daily returns of the 21 consecutive business days after drawdowns ending dates (black line). Under the EMH, we would expect no abnormal returns after these events, where daily returns should behave accordingly to the sample average returns (straight lines on graphs). Figure 3 presents the same information for drawups. As the financial time series often show ARCH (autoregressive conditional heteroscedasticity) structures, we can observe periods where high severity drawdowns and drawups tend to cluster together.

Figure 2: Cumulative returns after drawdowns



Cumulative returns after drawdowns (left) and average cumulative returns after drawdons (right). Gray lines show values for the whole data set and black lines only for periods after a drawdown greater or equal than 3σ of daily returns os each stock market index is observed

Figure 3: Cumulative returns after drawups - Developed countries and Emerging markets



Average cumulative returns after drawdons (right). Gray lines show values for the whole data set and black lines only for periods after a drawup greater or equal than 3σ of daily returns os each stock market index is observed

4.2 Estimation Results

Table 8 presents the regression estimates of abnormal daily returns following large drawdowns. The columns represent different time spans, from 2 to 21 business days, and the 2 blocks of estimates assume different definitions for large returns, relative to the standard deviation of the daily log returns series (σ). Table 9 presents the same estimates for abnormal daily returns following large drawups. Augmented Dickey-Fueller test cannot reject the hypothesis that indexes daily return series are stationary. The time horizons in our sample are long enough to capture different states of the market, including widely documented crisis periods. In general, we observe a greater occurrence of large drawups than large drawdowns.

4.2.1 Abnormal Returns Following Drawdowns

Overall, the majority of indexes presented significant cumulative abnormal returns for at least one time window following an event of large drawdown. FTSE is the only index that showed no evidence of abnormal returns in response to drawdowns of magnitude between 2σ and 3σ, whereas SX5E, FTSE, MEXBOL and KOSPI showed no evidence of abnormal returns following drawdowns of magnitude higher or equal that 3σ, providing evidence supporting market efficiency hypothesis.

The DJIA is the index with largest number of significant estimates, related to the period of 3, 4, 5, 10 and 21 business days after the business day following drawdowns' ending dates. The second day after drawdons' ending dates show significant abnormal returns only in the case of drawdowns with severity higher than 3σ of daily returns. S&P500 and NASDAQ, the other two US stock market indexes, also presented significant estimates for a lower number of periods after drawdowns. When considering drawdowns of lower magnitude (2 to 3 σ), the three US indexes (DJIA, S&P500 and NASDAQ) present results similar to previous empirical studies reporting subsequent reversals[15], providing additional support for the overreaction hypothesis. We find evidence of reversals also for IBOVESPA and MEXBOL. SX5E, HSI, JCI and KOSPI, at the contrary, provide evidence of return continuation after drawdowns of this magnitude.

[15] Amini et al. (2013)

Considering larger drawdowns with severity equal to or higher than 3σ, nevertheless, it is interesting to observe that all US indexes show evidence of return continuation behaviour, which are consistent with the underreaction hypothesis. HSI and IBOVESPA also showed a return continuation pattern where JCI is the only index showing return reversals after these largest drawdowns.

In summary, the evidence regarding return behavior following large drawdowns is mixed, providing support for different hypothesis. Efficient market and overreaction hypotheses seems to be more prevalent for large drawdowns of lower magnitude and both the efficient market and the underreaction hypotheses for large drawdowns of highest magnitudes.

4.2.2 Abnormal Returns Following Drawups

On the side of large positive cumulative returns, the SX5E is the only index that showed no evidence of abnormal returns following drawups of magnitude between 2σ and 3σ. DJIA is also the index with the most significant estimates in the case of abnormal returns in response to large drawups, followed by the other US market indexes. SX5E, FTSE, HSI and IBOVESPA are the indexes showing no evidence of significant short-term abnormal returns for drawups with larger magnitude.

Except for one estimate of the S&P500 index, the US indexes results provide evidence for return continuation following drawups considering the two different groups of severities. Regarding the other stock markets, HSI, IBOVESPA, MEXBOL show evidence of return continuation, while FTSE shows a reversal pattern. JCI and KOSPI presented mixed results depending on the severity of drawups and the time window. For drawups of lower magnitude, for example, KOSPI index showed return continuation in the second business day following the event ending date and reversal in until the tenth business day after drawups ending date.

4.2.3 Combined Evidence on Drawdowns and Drawups

Therefere, for the US market, there seem to be a supporting evidence for UIH only for drawdowns and drawups of magnitude between 2σ and 3σ. Tail events seem to support the underreaction hypothesis which predicts return continuation after large price variation events, in which the information embedded in large consecutive price variations is not immediately incorporated into prices or may be positively correlated with following new information.

In the case of the US indexes, our results are in line with the findings from Nam et al. (2006) and Bali et al. (2008), that documented an asymmetry in the effects following negative and positive large returns. Both studies found that negative returns tend to revert more quickly than positive ones. However, contrarily to Bali et al. (2008), as abnormal returns after drawdowns of magnitude equal to or higher than 3σ are supportive of the underreaction hypothesis, our findings suggest that short term reversals tend to occur mostly after lower magnitude drawdowns.

Table 10 summarizes the results for each stock market index. EMH is supported by no significant estimates. Overreaction is supported by estimates showing reversal patterns and underreaction hypothesis, at the contrary, by estimates providing evidence of return continuation. The UIH is supported by evidence of significant subsequent positive return after large drawdowns and drawups.

Atasanova and Hudson (2008), Hudson et al. (2001) and Mazouz et al. (2009) have also documented asymmetries related to the size of large price changes used as triggers to observe following returns. In this work, as stated before, this asymmetries are observed only in the case of drawdowns in the US stock market indexes, supporting the overreaction hypothesis for events of magnitude between 2σ and 3σ and the underreaction hypothesis for larger magnitude events.

Table 8: GJR-GARCH estimates of abnormal returns after large drawdowns.

	NDD	DD2	DD3	DD4	DD5	DD10	DD21
2 to 3 σ							
DJIA	698	0.042	0.039***	0.053**	0.048**	0.031***	0.032***
		0.301	0.001	0.041	0.014	0.010	0.002
SP500	482	0.095**	0.050	0.032	0.042*	0.022	0.025***
		0.040	0.140	0.215	0.076	0.176	0.000
NASDAQ	242	0.036	0.034	-0.011	0.002	0.041***	0.035**
		0.599	0.459	0.780	0.941	0.000	0.011
SX5E	183	-0.078	-0.116	-0.087*	-0.036	-0.011	-0.044***
		0.356	0.672	0.097	0.503	0.704	0.007
FTSE	228	0.042	0.020	-0.011	0.004	0.021	0.008
		0.553	0.680	0.780	0.880	0.251	0.371
HSI	229	-0.032	-0.190**	-0.123	-0.052	-0.039	0.009
		0.751	0.017	0.136	0.881	0.368	0.753
IBOVESPA	132	0.120	0.170	0.161*	0.160**	0.067	0.027*
		0.509	0.119	0.062	0.026	0.129	0.088
MEXBOL	118	0.076	0.111*	0.077	0.128*	0.054*	0.030*
		0.544	0.056	0.346	0.073	0.079	0.059
JCI	129	0.266	0.058	0.073	0.068	-0.017*	0.032
		0.186	0.612	0.833	0.165	0.100	0.646
KOSPI	235	-0.029	-0.100***	-0.097	-0.065	-0.010	-0.022
		0.744	0.001	0.382	0.299	0.598	0.281
≥ 3 σ							
	NDD	DD2	DD3	DD4	DD5	DD10	DD21
DIA	708	-0.214***	-0.160***	-0.131***	-0.087***	-0.050***	-0.015*
		0.000	0.000	0.000	0.001	0.002	0.078
SP500	537	-0.058	-0.063	-0.040	-0.031***	-0.009	-0.001
		0.384	0.184	0.308	0.000	0.636	0.938
NASDAQ	305	0.097	0.002	-0.019	-0.028	-0.043***	-0.023
		0.234	0.965	0.688	0.524	0.003	0.218
SX5E	192	-0.056	-0.045	-0.006	0.021	-0.002	0.029
		0.681	0.611	0.926	0.791	0.963	0.287
FTSE	196	0.101	0.063	0.019	0.013	-0.021	0.034
		0.277	0.956	0.644	0.786	0.570	0.176
HSI	256	-0.455	-0.291**	-0.161*	-0.096	-0.119***	-0.054
		0.061	0.020	0.096	0.237	0.001	0.223
IBOVESPA	113	-0.142	-0.028	0.065	0.119	-0.176***	-0.035
		0.586	0.864	0.565	0.336	0.000	0.168
MEXBOL	151	0.111	0.039	-0.027	-0.054	0.006	0.031
		0.491	0.732	0.757	0.475	0.896	0.317
JCI	162	0.420***	0.269	0.181**	0.135*	0.055	0.003
		0.000	0.359	0.033	0.062	0.236	0.772
KOSPI	273	0.011	-0.050	0.015	0.078	0.007	-0.010
		0.934	0.565	0.813	0.113	0.851	0.672

*, ** and *** denotes statistical significance at the 10.0%, 5.0% and 1.0% significance level, respectively. NDD represents the number of drawdowns in the sample. DDN shows estimates in the period span comprised by the second and the N-iest business day after drawdons' ending dates. Large drawdowns represented by magnitudes between 2 and 3 standard deviations of the daily series returns (top) and magnitudes higher or equal than 3 standard deviations of the daily series returns (bottom). For each index, numbers in the top line are the abnormal return estimates and numbers in the bottom line are the robust p-values computed based on White (1982).

Table 9: GJR-GARCH estimates of abnormal returns after large drawups.

	NDU	DU2	DU3	DU4	DU5	DU10	DU21
2 to 3 σ							
DJIA	826	0.005	0.026**	0.036***	0.028*	0.018**	0.022***
		0.989	0.035	0.000	0.072	0.014	0.008
SP500	612	-0.006	0.023**	0.009	-0.002	-0.006***	0.006
		0.120	0.027	0.696	0.914	0.005	0.466
NASDAQ	327	-0.059	0.012***	0.023*	-0.000	-0.002	-0.009
		0.392	0.002	0.052	0.986	0.901	0.329
SX5E	214	0.006	-0.032	-0.025	-0.029	0.028	0.021
		0.863	0.524	0.541	0.462	0.515	0.381
FTSE	255	-0.039***	-0.069	-0.041	-0.035	-0.014	0.013
		0.000	0.119	0.221	0.237	0.534	0.348
HSI	289	-0.032	0.055	0.045	0.034*	0.017	-0.049
		0.716	0.419	0.538	0.062	0.414	0.383
IBOVESPA	179	-0.073	-0.096	0.001	-0.019	0.020*	0.009
		0.587	0.322	0.995	0.777	0.098	0.763
MEXBOL	144	-0.133	-0.048	-0.008	-0.010	0.027*	0.034
		0.183	0.486	0.884	0.821	0.088	0.108
JCI	150	0.047	0.050	0.072	0.099**	0.190***	0.162***
		0.603	0.215	0.349	0.047	0.002	0.000
KOSPI	256	0.148**	0.050	-0.020	-0.006	-0.034***	-0.018
		0.038	0.332	0.624	0.866	0.003	0.249
≥ 3 σ							
	NDU	DU2	DU3	DU4	DU5	DU10	DU21
DIA	756	0.138***	0.142***	0.103***	0.064***	0.034**	0.008
		0.003	0.000	0.000	0.000	0.012	0.178
SP500	548	0.181***	0.130***	0.072**	0.056***	0.015	-0.006
		0.000	0.003	0.021	0.006	0.415	0.555
NASDAQ	336	0.036***	0.086***	0.038***	0.018	0.034**	0.040***
		0.002	0.000	0.000	0.357	0.046	0.000
SX5E	190	0.010	-0.014	-0.001	-0.032	-0.009	-0.003
		0.919	0.837	0.984	0.171	0.749	0.898
FTSE	223	0.046	0.043	-0.024	-0.004	0.034	0.004
		0.474	0.442	0.555	0.918	0.863	0.800
HSI	304	0.034	0.075	0.028	-0.004	0.011	0.010
		0.764	0.428	0.741	0.956	0.809	0.767
IBOVESPA	133	0.020	-0.003	-0.012	0.021	0.036	0.071
		0.889	0.983	0.921	0.832	0.617	0.157
MEXBOL	182	0.054	0.119	0.082	0.059	0.035	0.051*
		0.632	0.154	0.222	0.297	0.351	0.059
JCI	193	-0.145	-0.097	-0.110***	-0.068	-0.001	0.083**
		0.257	0.372	0.005	0.789	0.991	0.019
KOSPI	294	0.165*	0.132	0.077	0.038	0.066*	0.042
		0.093	0.188	0.176	0.352	0.068	0.366

*, ** and *** denotes statistical significance at the 10.0%, 5.0% and 1.0% significance level, respectively. NDU represents the number of drawups in the sample. DUN shows estimates in the period span comprised by the second and the N-iest business day after drawups' ending dates. Large drawdowns represented by magnitudes between 2 and 3 standard deviations of the daily series returns (top) and magnitudes higher or equal than 3 standard deviations of the daily series returns (bottom). For each index, numbers in the top line are the abnormal return estimated and numbers in the bottom line are the robust p-values computed based on White (1982).

Table 10: Summary of the estimation results.

Drawdwons (2 to 3 σ)	Effic. Market	Overreact.	Underreact.
DJIA	⋆	⋆	
SP500	⋆	⋆	
NASDAQ	⋆	⋆	
SX5E	⋆		⋆
FTSE	⋆		
HSI	⋆		⋆
IBOVESPA	⋆	⋆	
MEXBOL	⋆	⋆	
JCI	⋆		⋆
KOSPI	⋆		⋆

Drawups (2 to 3 σ)	Effic. Market	Overreact.	Underreact.	UIH
DJIA	⋆		⋆	⋆
SP500	⋆	⋆	⋆	⋆
NASDAQ	⋆		⋆	⋆
SX5E	⋆			
FTSE	⋆	⋆		
HSI	⋆		⋆	
IBOVESPA	⋆		⋆	⋆
MEXBOL	⋆		⋆	⋆
JCI	⋆		⋆	
KOSPI	⋆	⋆	⋆	

Drawdowns ($\geq 3\sigma$)	Effic. Market	Overeact.	Underreact.
DIA			⋆
SP500	⋆		⋆
NASDAQ	⋆		⋆
SX5E	⋆		
FTSE	⋆		
HSI	⋆		⋆
IBOVESPA	⋆		⋆
MEXBOL	⋆		
JCI	⋆	⋆	
KOSPI	⋆		

Drawups ($\geq 3\sigma$)	Effic. Market	Overeact.	Underreact.	UIH
DIA	⋆		⋆	
SP500	⋆		⋆	
NASDAQ	⋆		⋆	
SX5E	⋆			
FTSE	⋆			
HSI	⋆			
IBOVESPA	⋆			
MEXBOL	⋆		⋆	
JCI	⋆	⋆	⋆	⋆
KOSPI	⋆		⋆	

⋆ represents supporting evidence in regression estimates for at least one time horizon following drawdowns or drawups used in our study. Efficient Market Hypothesis means no abnormal results. Overreaction means return reversals and underreaction hypothesis means return continuation after large drawdowns or drawups. The Uncertain Information Hypothesis (UIH) is supported by the evidence when positive abnormal returns are observed both after large drawdowns and drawups.

4.2.4 Larger Duration Effects

We also estimate abnormal results following large drawdowns and drawups with durations equal or greater than 3 business days. In this case, we want to verify whether this time dependent behavior of consecutive negative or positive returns for periods with larger durations may influence the pattern of abnormal returns observed after these events. Tables 12 and 13 in the Appendix show GJR-GARCH estimates for abnormal returns following large drawdons and drawups, respectively. As a whole, we could not find any difference from patterns observed in the biggest sample, with drawdowns and drawups of all durations. US indexes tend to provide evidence supporting the same hypothesis as the evidence above mentioned. HSI and IBOVESPA, for instance, also show significant negative estimates for the ten business days following the second business day after drawdowns' ending dates in both samples with all durations and durations higher than 2 business days, for events with magnitude equal or higher than 3σ of daily series returns. We also did not observe significant differences in drawups' estimates.

4.2.5 Testing for Abnormal Returns at Ending Dates

We also use the same dummy approach to test whether positive and negative returns in the business days after drawdowns' and drawups' ending dates present a significant higher magnitude than average positive and negative returns. For each day t in the sample of daily returns, $D_{t,neg}$ is the dummy variable that equals 1 if t presents a negative return and 0 otherwise. $D_{t,1}$ is the dummy variable that equals 1 if t is the first business day after the event end date and 0 otherwise. Abnormal returns for the first business day after the events is then tested with the estimation of the following regression for each index daily log return r_t, assuming GJR-GARCH innovations as in eq.(3):

$$logr_t = \alpha + \phi_{neg} D_{t,neg} + \phi_1 D_{t,1} + \epsilon_t \tag{4}$$

The majority of indexes present abnormal returns at the business day immediately after the ending dates of drawdowns and drawups, showing that daily positive and negative returns after both events, respectively, present magnitudes statistically higher than average daily positive and negative returns. All estimates are positive, showing that ending dates positive returns after drawdowns are higher than average positive returns and also that ending dates negative returns after drawups are lower in severity than higher than average negative returns.

For events of larger severity (equal or greater than 3σ), ending dates of drawdowns present statistically significant abnormal returns for every index in the sample, whereas only S&P500, NASDAQ, HSI and KOSPI presented significant results for drawups' ending dates' returns. For those 4 indexes, nevertheless, we observe that S&P500, HSI and KOSPI show negative estimates, showing differences in ... according to the severity of drawups.

Table 11: GJR-GARCH estimates of abnormal returns in the business day following large drawdowns and drawups.

2 to 3 σ	Drawdowns	Drawups
DJIA	0.112***	0.100***
	0.000	0.000
SP500	0.193***	0.048***
	0.000	0.000
NASDAQ	0.171***	0.082**
	0.000	0.013
SX5E	0.220	0.104**
	0.179	0.017
FTSE	0.166***	0.030***
	0.000	0.000
HSI	0.270***	0.151***
	0.001	0.000
IBOVESPA	0.145	0.087
	0.222	0.291
MEXBOL	0.250**	0.082***
	0.025	0.004
JCI	0.308	0.009
	0.167	0.774
KOSPI	0.115	0.115***
	0.359	0.000

$\geq 3\sigma$	Drawdowns	Drawups
DJIA	0.388***	-0.083
	0.000	0.152
SP500	0.446***	-0.021***
	0.000	0.000
NASDAQ	0.354***	0.091***
	0.000	0.000
SX5E	0.653***	-0.037
	0.000	0.777
FTSE	0.395***	0.058
	0.000	0.455
HSI	1.294***	-0.255**
	0.000	0.039
IBOVESPA	1.346***	-0.095
	0.000	0.528
MEXBOL	0.645***	-0.149
	0.000	0.451
JCI	0.617***	-0.270
	0.010	0.217
KOSPI	0.733***	-0.180***
	0.000	0.001

*, ** and *** denotes statistical significance at the 10.0%, 5.0% and 1.0% significance level, respectively. NDU represents the number of drawups in the sample. DUN shows estimates in the period span comprised by the second and the N-iest business day after drawups' ending dates. Large drawdowns represented by magnitudes between 2 and 3 standard deviations of the daily series returns (top) and magnitudes higher or equal than 3 standard deviations of the daily series returns (bottom). For each index, numbers in the top line are the abnormal return estimated and numbers in the bottom line are the robust p-values computed based on White (1982).

5 Conclusion

In this study, we have investigated short-term abnormal returns in 10 stock market indexes following large price variations. We propose a novel approach and use drawdowns and drawups as event triggers. As these measures are not computed within a fixed time horizon, they are flexible to capture time-dependent subordinated processes (local dependence) that could be driving a market under or overreaction. We use the dummy variable approach similar to Karafiath (1988) and Mazouz et al. (2009) for time periods from 1 to 21 business days after the event ending dates. To circumvent restrictive assumptions on standard OLS estimation, we assume residual variance in the regressions to follow the GJR-GARCH model proposed by Glosten et al. (1993), which leads to higher estimation efficiency and avoids invalid inferences due to volatility clustering close to events dates.

The results show a great variety of estimates across the different stock market indexes in the sample, providing evidence that price behavior after large drawdowns and drawups varies according to country specific market features. This interpretation is also supported by the very similar results presented by the three US indexes used in this work. Similarly to previous empirical literature, we do not provide conclusive evidence on short-term predictability of stock market returns following large price variations. The Efficient Market Hypothesis is supported by the majority of estimates. Results also providence stronger support for underreation hypothesis than overreaction, with the highest prevalence of return continuations than reversals. Evidence for UIH is present is some markets, mainly after events of lower magnitude. As the UIH is an explanation based on market rationality, it seems natural that results provide evidence for behavioral biases explanations considering drawdowns and drawups for greater magnitude.

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Appendix

Table 12: GJR-Garch Estimates of Abnormal Returns After Large Drawdowns - durations greater than 3 standard deviations

2 to 3 σ							
	NDD	DD2	DD3	DD4	DD5	DD10	DD21
DJIA	400	0.018	0.028	0.050***	0.043*	0.018**	0.030***
		0.723	0.310	0.000	0.069	0.022	0.000
SP500	290	0.075	0.028	0.006	0.034*	0.019	0.020***
		0.160	0.429	0.813	0.083	0.352	0.000
NASDAQ	119	0.042	0.051	-0.017	-0.023	0.035	0.025**
		0.594	0.403	0.713	0.564	0.148	0.012
SX5E	91	-0.077	-0.070	-0.061	-0.007***	0.026	-0.027***
		0.599	0.305	0.806	0.009	0.375	0.006
FTSE	120	0.078	0.023	-0.010	0.028	0.016	0.017***
		0.398	0.704	0.773	0.524	0.446	0.006
HSI	131	0.035	-0.140	-0.118	-0.056	-0.030***	0.010***
		0.840	0.154	0.196	0.726	0.000	0.000
IBOVESPA	85	0.017	0.013	0.092	0.114	0.054	-0.000
		0.897	0.884	0.310	0.202	0.784	0.997
MEXBOL	77	0.119	0.191	0.111	0.182***	0.097***	0.068
		0.452	0.581	0.060	0.001	0.000	0.132
JCI	85	0.185	0.014	0.044	0.045	-0.026	0.030***
		0.217	0.878	0.335	0.744	0.912	0.002
KOSPI	139	-0.046	-0.149	-0.136***	-0.091***	-0.025	-0.046
		0.658	0.242	0.000	0.000	0.446	0.079
$\geq 3\ \sigma$							
	NDD	DD2	DD3	DD4	DD5	DD10	DD21
DIA	510	-0.199***	-0.161**	-0.131***	-0.090***	-0.055***	-0.018**
		0.001	0.041	0.000	0.000	0.000	0.027
SP500	386	-0.008	-0.034***	-0.028	-0.026	0.003	-0.004
		0.916	0.003	0.112	0.457	0.628	0.781
NASDAQ	238	0.109	0.007	0.006	-0.007	-0.023	-0.020
		0.201	0.915	0.846	0.876	0.436	0.299
SX5E	142	-0.048	-0.074	0.001	0.024	-0.005	0.020
		0.744	0.495	0.992	0.241	0.897	0.509
FTSE	151	0.046	0.018	0.010	0.006	-0.006	0.031
		0.643	0.807	0.905	0.859	0.849	0.109
HSI	209	-0.454**	-0.304**	-0.185*	-0.107	-0.129**	-0.046
		0.033	0.025	0.075	0.226	0.042	0.280
IBOVESPA	90	-0.217	-0.139	-0.034	0.078	-0.182**	-0.041
		0.457	0.461	0.827	0.330	0.017	0.260
MEXBOL	121	0.072	-0.027	-0.058	-0.059	-0.006	0.027
		0.688	0.834	0.563	0.487	0.901	0.479
JCI	145	0.383***	0.254	0.173	0.119*	0.046	0.008
		0.001	0.153	0.316	0.093	0.565	0.496
KOSPI	198	-0.009	-0.093	-0.013	0.064	0.016	-0.001
		0.953	0.340	0.859	0.271	0.644	0.956

*, ** and *** denotes statistical significance at the 10.0%, 5.0% and 1.0% significance level, respectively. NDD represents the number of drawdowns in the sample. DDN shows estimates in the period span comprised by the second and the N-iest business day after drawdons' ending dates. Large drawdowns represented by magnitudes between 2 and 3 standard deviations of the daily series returns (top) and magnitudes higher or equal than 3 standard deviations of the daily series returns (bottom). For each index, numbers in the top line are the abnormal return estimated and numbers in the bottom line are the robust p-values computed based on White (1982).

Table 13: GJR-Garch Estimates of Abnormal Returns After Large Drawdowns - durations greater than 3 standard deviations

	NDU	DU2	DU3	DU4	DU5	DU10	DU21
2 to 3 σ							
DJIA	544	-0.012	0.009	0.035**	0.031	0.007	0.0163*
		0.466	0.388	0.025	0.153	0.542	0.066
SP500	391	-0.006	0.018	0.010	-0.001	-0.005***	0.006*
		0.883	0.472	0.433	0.913	0.003	0.097
NASDAQ	228	-0.074	0.002	0.016	-0.002	-0.007	-0.014*
		0.213	0.897	0.339	0.748	0.280	0.093
SX5E	125	0.030	-0.033	-0.026	-0.034***	0.016	0.002
		0.697	0.640	0.592	0.007	0.589	0.934
FTSE	145	0.004	-0.050	-0.035**	-0.031	0.005	0.014
		0.941	0.248	0.039	0.428	0.556	0.421
HSI	199	0.004	0.073	0.063	0.044	0.008	-0.053***
		0.972	0.232	0.155	0.379	0.364	0.000
IBOVESPA	107	-0.070	-0.092	0.010	-0.015	0.033***	-0.027
		0.619	0.261	0.911	0.838	0.000	0.352
MEXBOL	96	-0.093	0.014	0.034	0.025	0.024	0.041**
		0.475	0.836	0.576	0.626	0.403	0.030
JCI	121	0.069	0.063	0.081	0.117*	0.198***	0.158
		0.771	0.368	0.322	0.056	0.001	0.055
KOSPI	140	0.219***	0.094***	0.016	-0.003	-0.023	-0.020***
		0.009	0.000	0.719	0.728	0.588	0.007
$\geq 3\ \sigma$							
	NDU	DU2	DU3	DU4	DU5	DU10	DU21
DIA	550	0.148***	0.151***	0.110***	0.068***	0.045***	0.006
		0.002	0.002	0.000	0.002	0.000	0.337
SP500	384	0.175***	0.134***	0.075*	0.053***	0.029*	-0.003
		0.004	0.007	0.051	0.000	0.097	0.837
NASDAQ	264	0.041	0.084**	0.038	0.018	0.035***	0.041***
		0.488	0.040	0.244	0.569	0.000	0.006
SX5E	137	0.024	0.004	0.009	-0.028	0.004	0.012
		0.816	0.972	0.878	0.660	0.889	0.258
FTSE	168	0.033	0.047	-0.021	0.012	0.035	0.003
		0.637	0.377	0.459	0.124	0.185	0.876
HSI	232	0.020*	0.081	0.070	0.031	0.028	0.016
		0.067	0.418	0.426	0.654	0.556	0.790
IBOVESPA	111	0.051	0.007	-0.002	0.033	0.067	0.064
		0.822	0.964	0.988	0.756	0.342	0.384
MEXBOL	143	0.061	0.112	0.075	0.059	0.032	0.033
		0.614	0.354	0.376	0.367	0.464	0.232
JCI	162	-0.146	-0.086	-0.110	-0.067	-0.016	0.076
		0.249	0.394	0.529	0.472	0.832	0.219
KOSPI	241	0.214**	0.159*	0.111***	0.081	0.087**	0.045
		0.037	0.047	0.000	0.157	0.021	0.171

*, ** and *** denotes statistical significance at the 10.0%, 5.0% and 1.0% significance level, respectively. NDU represents the number of drawups in the sample. DUN shows estimates in the period span comprised by the second and the N-iest business day after drawups' ending dates. Large drawdowns represented by magnitudes between 2 and 3 standard deviations of the daily series returns (top) and magnitudes higher or equal than 3 standard deviations of the daily series returns (bottom). For each index, numbers in the top line are the abnormal return estimated and numbers in the bottom line are the robust p-values computed based on White (1982).