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 of the stock markets, which are mostly based on fixed-time price variations, have inconclusive findings: evidence of short-term predictability varies according to different samples and methodologies. We propose a novel approach and use drawdowns and drawups as triggers, 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 subordinate, time-dependent processes that could drive market under- or overreaction. Most estimates in our results support the efficient market hypothesis. The underreaction hypothesis receives stronger support than does overreaction, with higher prevalence of return continuations than reversals. Evidence for the uncertain information hypothesis is present in some markets, mainly after lower-magnitude events.

Keywords: Market efficiency; Abnormal returns; Drawdowns.

JEL Code: G1, G14, G15.

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1. Introduction

In 2008, when Queen Elizabeth II asked a group of professors at the London School of Economics why nobody had noticed the financial crisis coming,1 Her Majesty was probably unaware 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), who developed the mathematics of Brownian motion as a model for stock price variations and concluded they followed a random walk. Since then, the randomness of the financial markets has become a subject of great interest and scrutiny among academics and market participants.

Half a century ago, Prof. Eugene F. Fama published his first broad review of the theoretical and empirical literature on this subject. Even at that time, he already recognized the area was “so bountiful” that he apologized

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1Why did nobody notice it? (Zingales, 2012).
for any missing references (Fama, 1970). He consolidated and popularized the concept of an efficient market as one “in which prices always fully reflect available information” and defined the classic taxonomy that distinguishes the three different forms of market efficiency: weak (past return), semi-strong (public information) and strong (public and private information), according to the type of information used to predict future prices.

Since then, the academic debate has been driven around what is now well-known as the “efficient market hypothesis” (EMH), which evolved from the random walk theory of asset prices (Fama, 1965; Samuelson, 1965). As Ball (2009) explains, 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 price fluctuations are driven solely by the arrival of new and relevant information. Rational expectation plays a central role in 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 prevent prices from diverging from market equilibrium (Friedman, 1953).

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. They suggest that future research could benefit from using different ways to define large returns, such as looking at those conditional on other factors.

Following that idea, we propose using drawdowns and drawups as triggers, in order to investigate the existence of short-term abnormal returns in stock markets, using ten 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. Unlike fixed-time measures such as daily, weekly or monthly returns, the duration of drawdowns and drawups varies randomly according to investor behavior. As these measures are not computed within a fixed time horizon, they are flexible enough to capture subordinate, time-dependent processes (local dependence) that could drive investors’ under- or overreaction.

As emphasized by Mandelbrot (1963), for price return 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 subordinate, time-dependent process. The process could be related to market microstructure variables, such as trading volume or number of trades, which are ultimately related to investor behavior.
Dacorogna et al. (1996), Levitt (1998), Weron and Weron (2000), and Gerhard and Hautsch (2002) give examples of alternative ways to capture the dynamics of financial time series using the concept of elastic time. Using drawdowns and drawups may better enable us to understand market behavior, compared to fixed time statistics, especially those related to the occurrence of large returns (Mandelbrot, 1972; Johansen and Sornette, 2001; Mendes and Brandi, 2004).

We estimate 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 date. Residual variance is assumed to follow the GJR-GARCH model proposed by Glosten et al. (1993), which captures both GARCH structure and 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 inference caused by failure to capture market uncertainty variations close to event periods.

Our results show a great variety of estimates across the different stock market indexes in the sample. This variety is 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 majority of estimates support the efficient market hypothesis. Results also provide stronger support for the underreaction hypothesis than for overreaction, with a higher prevalence of return continuations than reversals. Evidence for the uncertain information hypothesis (UIH) is present in some markets, mainly after events of lower magnitude.

The remainder of the paper is organized as follows. The next section discusses the related literature. Section 3 presents the data and Section 4 discusses the methodology. Section 5 describes the empirical results, while the conclusion is presented in the last section.

2. Related literature

With the development of cognitive and social psychology, economists gained a better understanding of how biases in judgments and beliefs can affect the individual decision-making process, as well as market behavior as a whole. The field of “behavioral economics” also added many insights to the market efficiency debate, by incorporating new evidence on how human behavior departs from the hypothesis of rationality. Inspired by evidence from

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2See Kahneman and Tversky (1982) for an early reference.
Kahneman and Tversky (1979) that individuals tend to underweight base rate (prior) data and overweight recent information, DeBondt and Thaler (1985), in widely-known early research, find empirical evidence of long-term overreaction in the US stock market.

In a further review, Fama (1998) argues in favor of the efficient market hypothesis. He points out that observed anomalies tend to disappear over time or with improved research methodology. This would clearly make it impossible to obtain excessive and easy profits through stock market transactions.

Shiller (2003), in contrast, states that behavioral finance research may contribute to understanding markets’ sometimes-irrational behavior. Perhaps market-efficiency interpretations of abnormal events can lead to incorrect answers. As the author concludes, researchers may “distance ourselves from the presumption that financial markets always work well and that price changes always reflect genuine information.” From this perspective, studying market anomalies may help to support, for instance, improvements in information transparency (Healy and Palepu, 2001).

The first studies on short-term overreaction, however, yielded quite controversial results. While Arbel and Jaggi (1982) and Atkins and Dyl (1990) find no evidence to reject the EMH, Bremer and Sweeney (1991) find 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 lacks consensus on which of them prevails. Besides overreaction, another behavioral explanation, known as the underreaction hypothesis, assumes that new information is not immediately incorporated into market prices, causing near-term future returns to follow the direction of prior large price changes.

It is also possible that abnormal returns may be explained by no anomaly at all, based on the conventional rational expectations framework. Under the UIH, the systematic risk of stocks tends to increase concurrently with large price variations, which leads to a demand for higher expected returns from risk-averse rational investors (Brown et al., 1988). As a result, this hypothesis predicts return continuation after large price increases, and reversals after large drops. In addition, some explanations relate to market microstructure, such that spurious serial correlation may be caused by unsynchronized trading or bid-ask bounce effects (Cox and Peterson, 1994).

For Brazil’s stock market, Dourado and Tabak (2014) compare results from different studies and conclude that this topic is controversial in this country, as well. Using the most popular national stock index as the price reference, they provide evidence supporting market efficiency, in accordance

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3 Benou (2003).
with most recent results in the literature. Similar results were found by Saffi (2003), who concludes in favor of a weak form of the efficient market hypothesis, after observing predictions from technical analysis investment strategies. In contrast, Gaio et al. (2009) use time series techniques to show that the Brazilian market does not display a weak form of market efficiency.

Da Costa Jr. (1994) presents one of the earliest studies of overreaction in the Brazilian stock market. He investigates the period from 1970 to 1989, and finds evidence of price reversals in 2-year returns with magnitudes higher than those observed in the US market. Bonomo and DallAgnol (2003), testing results from adverse strategies, and Barbosa and Medeiros (2007), observing share price behavior after positive and negative shocks, present more recent evidence of overreaction in the local market.

3. Data sample

Data for this research is composed of daily closing prices of ten stock price indexes from eight 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); the Mexican stock exchange - MEXBOL (Mexico); the Indonesian stock exchange - JCI (Indonesia); and the Korean stock exchange - KOSPI 200 (Korea). We intentionally select data from the largest stock exchanges among developed and emerging economies to provide any preliminary anecdotal evidence of possible differences between these two groups of countries.

Daily returns are obtained using the natural logarithm of the ratio between the closing price of each business day and the closing price of the previous business day (multiplied by 100 to express percentage returns). Observation periods are different between indexes, but all series end on December 31, 2015. The DJIA is the 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 results are consistent with previously-documented stylized facts of stock market returns, such as negative skewness and excess kurtosis (Rydberg, 2000). Differences in the number of drawdowns and drawups are explained by our strict definition, by which consecutive days with the same price mark the end 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 |
|---------|----|-----------|------|--------|------|------|---------|------|----------|
| DJIA    | 28885 | 1900-06-27 | 0.03 | 0.05   | -22.61 | 15.34 | 1.13     | 0.42 | 21.11    |
| SP500   | 21972 | 1928-01-03  | 0.03 | 0.05   | -20.47 | 16.61 | 1.18     | 0.08 | 17.36    |
| NASDAQ  | 11194 | 1971-02-08  | 0.04 | 0.11   | -11.35 | 14.17 | 1.24     | 0.07 | 10.08    |
| SXSE    | 7341  | 1987-01-01  | 0.03 | 0.05   | -7.93  | 11.00 | 1.32     | 0.01 | 6.02     |
| FTSE100 | 7969  | 1984-01-04  | 0.03 | 0.06   | -12.22 | 9.84  | 1.10     | 0.31 | 8.94     |
| HSI     | 11289 | 1964-08-31  | 0.07 | 0.06   | -33.33 | 19.79 | 1.90     | 0.16 | 20.14    |
| IBOVESPA| 5309  | 1994-01-03  | 0.12 | 0.11   | -15.82 | 33.41 | 2.32     | 0.99 | 15.34    |
| MEXBOL  | 5350  | 1994-01-20  | 0.07 | 0.07   | -13.34 | 12.92 | 1.54     | 0.19 | 6.97     |
| JCI     | 7859  | 1983-04-05  | 0.06 | 0.02   | -20.17 | 49.64 | 1.61     | 4.72 | 139.80   |
| KOSPI   | 9640  | 1980-01-05  | 0.04 | 0.02   | -12.02 | 11.95 | 1.50     | 0.07 | 5.17     |

#### 3.1 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 $P_t$ is the asset price (index value) on day $t$ and $r_t = (P_t/P_{t-1} - 1)$ is the daily return on this same date. $P_t$ is said to be a local maximum when prices on the previous and following days are lower, $P_{t-1} < P_t > P_{t+1}$. A local minimum, conversely, is 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, drawdown severity may be computed in either of the following ways:

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

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 higher for emerging markets, which is consistent with the higher risk premia and volatilities observed in these higher-risk environments.

For developed markets, drawdown distributions seem to present a longer tail than drawup distributions. We can see the three largest drawdowns are more severe than the three largest drawups. In the case of emerging markets, it is quite the opposite, where the largest drawups are observed to have higher magnitudes than the largest drawdowns.

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4Drawups are defined analogously, considering positive returns.
3.1.1 The first dimension – magnitude

Drawdowns and drawups are measured in two dimensions: magnitude and duration. Table 3 shows drawdown and drawup frequencies according to different severity ranges, based on multiples of the sample standard deviation of daily returns for each index. In general, the stock market indexes present similar distributions, in which the most frequent severities of drawdowns and drawups are concentrated in the 0-1σ range, with relative frequencies from 55% to 60%. Fewer observations occur at higher severity ranges. Drawups seem to be concentrated in higher severity ranges than drawdowns; we observe frequencies in the first range categories around 50%. The JCI Index seems to be an outlier in this dimension, with more drawdowns and drawups in the lowest severity range, compared to the other indexes.

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

Table 2

| index       | NDD | meanDD | min  | min2 | min3 | NDU | meanDU | max  | max2 | max3 |
|-------------|-----|--------|------|------|------|-----|--------|------|------|------|
| DJIA        | 6947| −1.48  | −30.68| −28.22| −23.62| 6992| 1.58   | 22.96| 18.57| 17.44|
| SP500       | 5185| −1.53  | −28.51| −22.90| −22.74| 5210| 1.65   | 22.46| 20.83| 17.72|
| Nasdaq Comp.| 2434| −1.75  | −25.30| −24.61| −22.63| 2435| 1.95   | 16.32| 14.17| 13.95|
| SX5E        | 1827| −1.74  | −19.68| −17.52| −15.89| 1829| 1.85   | 17.47| 15.04| 13.27|
| FTSE100     | 1984| −1.48  | −21.73| −14.62| −13.69| 1989| 1.59   | 17.75| 15.43| 11.22|
| HSI         | 2687| −2.40  | −41.69| −38.57| −32.16| 2689| 2.67   | 48.24| 38.75| 29.85|
| Ibovespa    | 1307| −2.92  | −34.63| −31.18| −31.01| 1307| 3.36   | 48.93| 41.80| 35.05|
| MexBol      | 1241| −2.11  | −20.75| −20.59| −18.85| 1241| 2.39   | 22.99| 17.90| 15.07|
| JCI         | 1679| −1.87  | −32.09| −22.93| −22.83| 1702| 2.11   | 68.67| 35.85| 23.30|
| KOSPI       | 2237| −2.09  | −25.53| −22.27| −18.67| 2240| 2.26   | 21.09| 20.53| 19.32|

Min denotes the largest drawdown, min2 the second-largest and min3 the third-largest. Max denotes the largest drawup, max2 the second-largest and max3 the third-largest.

3.1.2 The second dimension – duration

Table 4 presents the observed frequencies of drawdown and drawup durations, described in business days. The longest duration of consecutive negative returns corresponds to the NASDAQ’s 16 business days, for developed economies, and 19 business days in the JCI, for emerging markets. On the gains side, the NASDAQ presents the longest drawup duration, equivalent to 19 business days. For all indexes, the distributions of drawdown durations seem to be more concentrated in the shortest duration, 1 business day. The observed frequencies of drawups present higher values for longer durations than those of drawdowns. We will provide additional analysis focusing on
Table 3  
Number of drawdown and drawup observations by magnitude ranges

| drawdowns         | total  | 0-1σ | 1-2σ | 2-3σ | 3-4σ | 4-5σ | 5-6σ | >6σ |
|-------------------|--------|------|------|------|------|------|------|-----|
| DJIA              | 6947   | 4022 | 1524 | 704  | 310  | 162  | 82   | 143 |
| SP500             | 5185   | 3048 | 1123 | 492  | 235  | 113  | 71   | 103 |
| Nasdaq Comp.      | 2434   | 1391 | 498  | 245  | 120  | 69   | 40   | 71  |
| SXSE              | 1827   | 1037 | 418  | 181  | 83   | 40   | 30   | 38  |
| FTSE100           | 1984   | 1091 | 470  | 230  | 84   | 50   | 28   | 31  |
| NYK               | 2755   | 1553 | 625  | 287  | 134  | 60   | 46   | 50  |
| HSI               | 2687   | 1613 | 595  | 231  | 105  | 50   | 36   | 57  |
| Ibovespa          | 1307   | 751  | 317  | 131  | 49   | 22   | 15   | 22  |
| MexBol            | 1241   | 688  | 284  | 122  | 67   | 28   | 25   | 27  |
| JCI               | 1679   | 1138 | 253  | 129  | 54   | 40   | 22   | 43  |
| KOSPI             | 2237   | 1222 | 513  | 235  | 116  | 74   | 30   | 47  |

| drawups           | total  | 0-1σ | 1-2σ | 2-3σ | 3-4σ | 4-5σ | 5-6σ | >6σ |
|-------------------|--------|------|------|------|------|------|------|-----|
| DJIA              | 6992   | 3552 | 1873 | 824  | 393  | 161  | 83   | 106 |
| SP500             | 5210   | 2657 | 1402 | 618  | 279  | 111  | 55   | 88  |
| NASDAQ            | 2435   | 1149 | 629  | 325  | 143  | 84   | 41   | 64  |
| SXSE              | 1829   | 910  | 517  | 218  | 86   | 48   | 21   | 29  |
| FTSE100           | 1989   | 972  | 541  | 257  | 116  | 51   | 19   | 33  |
| NYK               | 2754   | 1370 | 744  | 329  | 152  | 71   | 45   | 43  |
| HSI               | 2689   | 1420 | 684  | 289  | 126  | 71   | 44   | 55  |
| IBOVESPA          | 1307   | 650  | 349  | 180  | 61   | 24   | 14   | 29  |
| MEXBOL            | 1241   | 617  | 300  | 149  | 82   | 39   | 22   | 32  |
| JCI               | 1702   | 1021 | 342  | 151  | 77   | 44   | 20   | 47  |
| KOSPI             | 2240   | 1159 | 532  | 261  | 114  | 73   | 31   | 70  |

Drawdown and drawup frequencies according to different severity ranges, based on multiples of the sample standard deviation of daily log-returns of each index.

drawdowns and drawups with duration greater than 2 business days, trying to capture information from events that persist through longer time periods. We do not find any specific pattern comparing figures from developed and emerging markets.

### 3.1.3 Relationship between two dimensions

It is reasonable to assume that longer drawdowns and drawups provide returns of higher magnitudes. Among the stock market indexes in our sample, correlations between drawdown duration and severity lie around -0.5 to -0.7, and drawup correlations are calculated around 0.5 to 0.7. Table 5 presents the distribution of drawdown and drawup 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 are more prevalent. This same pattern is observed for the other indexes in our dataset.

In addition, when we observe the average daily returns of drawdowns
and drawups with different durations, we verify that not only do drawdown magnitudes tend to grow with duration, but also the average daily severity of drawdowns increases with duration. Regarding drawups, we observe the opposite: average daily returns of drawups decrease with duration. Compar-

### Table 4

| drawdowns | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | ≥ 10 | max |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|
| DJIA      | 49.91 | 25.78 | 13.04 | 5.77 | 2.99 | 1.41 | 0.63 | 0.32 | 0.04 | 0.10 | 12.00 |
| SP500     | 49.43 | 25.67 | 13.64 | 5.82 | 2.99 | 1.39 | 0.58 | 0.25 | 0.12 | 0.12 | 12.00 |
| NASDAQ    | 49.10 | 24.90 | 13.23 | 5.96 | 3.66 | 1.56 | 0.82 | 0.49 | 0.12 | 0.16 | 16.00 |
| SXX5E     | 51.01 | 26.44 | 12.59 | 4.87 | 3.07 | 1.15 | 0.38 | 0.22 | 0.16 | 0.11 | 11.00 |
| FTSE100   | 51.36 | 24.45 | 14.26 | 5.65 | 2.62 | 1.06 | 0.45 | 0.05 | 0.05 | 0.05 | 11.00 |
| HSI       | 48.86 | 25.01 | 13.58 | 6.33 | 3.24 | 1.67 | 0.67 | 0.45 | 0.07 | 0.11 | 11.00 |
| IBOVESPA  | 49.89 | 26.93 | 12.55 | 5.51 | 3.14 | 1.22 | 0.38 | 0.23 | 0.15 | 0.00 | 9.00  |
| MEXBOL    | 48.51 | 24.01 | 14.50 | 6.29 | 3.38 | 1.85 | 1.05 | 0.16 | 0.24 | 0.00 | 9.00  |
| JCI       | 51.28 | 22.45 | 11.91 | 5.54 | 4.17 | 1.91 | 1.25 | 0.42 | 0.54 | 0.54 | 19.00 |
| KOSPI     | 47.61 | 25.35 | 11.98 | 6.93 | 4.16 | 2.19 | 0.98 | 0.45 | 0.22 | 0.13 | 11.00 |

† Last column presents maximum duration of drawdowns and drawups for each index.

### Table 5

| Distribution of drawdown and drawup durations† |
|---------------------------------------------|
| DJIA drawdowns total | 1σ  | 2σ  | 3σ  | 4σ  | 5σ  | 6σ  |
|-----------------------|-----|-----|-----|-----|-----|-----|
| 1 day                 | 0.50| 0.21| 0.11| 0.07| 0.05| 0.04|
| 2 days                | 0.26| 0.30| 0.24| 0.21| 0.20| 0.17|
| 3 days                | 0.13| 0.24| 0.25| 0.25| 0.24| 0.23|
| 4 days                | 0.06| 0.12| 0.17| 0.15| 0.15| 0.14|
| 5 days                | 0.03| 0.07| 0.11| 0.13| 0.13| 0.11|
| >5 days               | 0.03| 0.06| 0.11| 0.18| 0.23| 0.28|

| DJIA drawups total | 1σ  | 2σ  | 3σ  | 4σ  | 5σ  | 6σ  |
|---------------------|-----|-----|-----|-----|-----|-----|
| 1 day               | 0.45| 0.19| 0.11| 0.10| 0.09| 0.08|
| 2 days              | 0.26| 0.29| 0.20| 0.17| 0.16| 0.16|
| 3 days              | 0.14| 0.23| 0.22| 0.19| 0.13| 0.15|
| 4 days              | 0.07| 0.14| 0.20| 0.19| 0.19| 0.21|
| 5 days              | 0.04| 0.07| 0.12| 0.12| 0.12| 0.08|
| >5 days             | 0.04| 0.08| 0.16| 0.23| 0.31| 0.31|

† Samples with magnitudes higher than multiples of daily returns’ standard deviation - DJIA
ing the two groups of countries, we observe higher disparity among emerging markets and bigger variation of average daily returns for different durations. This seems to be a normal feature, due to the higher volatility and fatter tails observed in emerging stock markets.

4. Methodology

Large returns are defined based on the magnitude of drawdowns or drawups. Ranges of magnitude are computed for each index separately, according to the standard deviation of its sample daily returns (\( \sigma \)), as shown in Table 1. For drawdowns, the ranges are defined as \(-3\sigma \leq DD_{td} < -2\sigma\) and \(DD_{td} < -3\sigma\). Drawup ranges are defined similarly, as follows: \(2\sigma < DU_{tu} \leq 3\sigma\) and \(3\sigma < DU_{tu}\). The defined threshold of \(2\sigma\) helps limit our analysis to large price variations, and is consistent with previous studies related to stock market indexes.\(^5\)

Since these measures are computed over different time spans, the event end date is taken as the day of the last negative return for a drawdown (or the local minimum day) or the last positive return for 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 day after the event end date and 0 otherwise. Dummy variables for windows greater than 2 business days are equal to 1 when the date is in the time window that ranges from the second business day immediately after the event to the specified maximum number of business days in the window. Formally, as defined by Mazouz et al. (2009), \(D_{t,2}, D_{t,3}, \ldots, D_{t,N}\) take value equal to 1 if \(t \in [+2, +2], [+2, +3], \ldots, [+2, +N]\) and 0 otherwise, where \([+2, +N]\) is the span of time from the second to the N-th business day after the event end date.

The presence of abnormal returns is investigated by estimating the following regression for each stock market index daily log return \(r_t\):

\[
\log r_t = \alpha + \phi_n D_{t,n} + \epsilon_t, \tag{2}
\]

where \(\alpha\) is the constant, \(\phi_n\) are the coefficients of the dummy variables \(D_{t,n}\), and \(\epsilon_t \sim N(0, \sigma^2_t)\). To account for well-documented patterns in the volatility of stock index returns\(^6\) 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:

\(^5\)See Lasfer et al. (2003) and Nam et al. (2006) for examples.
\(^6\)See Black (1976), Cont (2001), Mandelbrot (1963), Clark (1973), among others.
\begin{equation}
    h_t^2 = \omega + (\delta + \nu 1_{t-1}) \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \gamma n D_{t,n},
\end{equation}

where $\omega$ is a constant, $\delta$ and $\beta$ are the conventional GARCH coefficients (Bollerslev, 1986), $\gamma$ is the asymmetry coefficient proposed by Glosten et al. (1993), and $1_{t-1}$ is the indicator variable, which is equivalent to 1 when $\varepsilon_{t-1} < 0$ and 0 otherwise. Cumulative abnormal returns associated with windows ending on the $n$-th business day after event end dates are estimated as $CAR_n = \phi_n \times (n - 1)$. We exclude the first business day after event end dates from previous dummies’ windows because, by definition, they show only positive returns in the case of drawdowns, and negative returns in the event of drawups. Also, as drawdowns and drawups are defined as a sequence of cumulative negative or positive returns, respectively, in the next section, we provide additional analysis to test for abnormal returns on drawdown and drawup end dates.

5. Empirical analysis

5.1 Preliminary investigation on returns after drawdowns and drawups

Figure 1 presents cumulative daily returns of the 21 consecutive business days after drawdowns with absolute severity equal to or higher than 3 standard deviations of sample daily returns, for each stock market index. In the left column, for each index, graphs show cumulative daily returns of the 21 consecutive business days after each business day of our sample (gray lines) and the cumulative daily returns of the 21 consecutive business days after drawdown end dates (black lines). In the right column, graphs show the average cumulative daily returns of the 21 consecutive business days after each business day of our sample (gray line) and the average cumulative daily returns of the 21 consecutive business days after drawdown end dates (black line). Under the EMH, we would expect no abnormal returns after these events, and daily returns should behave according to the sample average returns (straight lines on graphs). Figure 2 presents the same information of the average cumulative returns for drawups.

5.2 Estimation results

Table 6 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 two blocks of estimates assume different definitions for large returns, relative to the standard deviation of the daily log returns series ($\sigma$). Table 7 presents the same estimates for abnormal daily returns following large drawups. The augmented Dickey-Fuller test rejects...
the non-stationarity hypothesis for all daily return series in the sample. 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.

### 5.2.1 Abnormal returns following drawdowns

Overall, most indexes present significant cumulative abnormal returns for at least one time window following a large drawdown event. The FTSE is the only index that shows no evidence of abnormal returns in response to drawdowns of magnitude between $2\sigma$ and $3\sigma$, whereas SX5E, FTSE, MEXBOL and KOSPI show no evidence of abnormal returns following drawdowns of magnitude higher than or equal to $3\sigma$, providing evidence to support the market efficiency hypothesis.

The DJIA is the index with the largest number of significant estimates, related to the periods 3, 4, 5, 10, and 21 business days after the business day following drawdown end dates. The second day after drawdown end dates shows significant abnormal returns only in the case of drawdowns with severity higher than $3\sigma$ of daily returns. The S&P500 and NASDAQ, the other two US stock market indexes, also present significant estimates, for
fewer periods after drawdowns. Considering drawdowns of lower magnitude (2 to 3 $\sigma$), the three US indexes (DJIA, S&P500, and NASDAQ) present results similar to those of previous empirical studies reporting subsequent reversals,\(^7\) which provides additional support for the overreaction hypothesis. We also find evidence of reversals for IBOVESPA and MEXBOL. The SX5E, HSI, JCI, and KOSPI, in contrast, provide evidence of return continuation after drawdowns of this magnitude.

Considering larger drawdowns, with severity equal to or higher than 3$\sigma$, it is interesting to observe that all US indexes show evidence of return continuation behavior, consistent with the underreaction hypothesis. The HSI and IBOVESPA also show a return continuation pattern. The JCI is the only index that shows return reversals after these largest drawdowns.

Overall, the evidence regarding return behavior following large drawdowns is mixed, providing support for different hypotheses. The efficient market and overreaction hypotheses seem to prevail for large drawdowns of lower magnitude, and both the efficient market and the underreaction hypotheses for large drawdowns of higher magnitude.

Regarding the Brazilian index, specifically, results for lower-magnitude drawdowns are in line with the price reversals and overreaction patterns found by Da Costa Jr. (1994), Bonomo and Dall’Agnol (2003), and Barbosa and Medeiros (2007). Considering larger drawdowns, however, we observe new evidence of return continuation, suggesting that price information conveyed

\(^7\)Amini et al. (2013).
by these events may not be immediately incorporated into stock prices.

5.2.2 Abnormal returns following drawups

On the side of large cumulative positive returns, the SX5E is the only index that shows no evidence of abnormal returns following drawups of magnitude between $2\sigma$ and $3\sigma$. The DJIA is again the index with the most significant estimates in cases of abnormal returns in response to large drawups, followed by the other US market indexes. The SX5E, FTSE, HSI, and IBOVESPA show no evidence of significant short-term abnormal returns for drawups with larger magnitude.

Except for one estimate from the S&P500 index, the US indexes provide evidence for return continuation following drawups of both of these levels of severity. Out of the other stock markets, the HSI, IBOVESPA, and MEXBOL show evidence of return continuation, while FTSE shows a reversal pattern. The JCI and KOSPI present mixed results depending on the severity of drawup and time window. For drawups of lower magnitude, for example, the KOSPI index shows return continuation on the second business day following the drawup end date and reversal for the ten business days afterward.

As for Brazil’s stock market, results show some asymmetry in market behavior after positive and negative shocks. For lower-magnitude drawup events, of magnitude between $2\sigma$ and $3\sigma$, instead of the price reversals observed after drawdowns, we find evidence of return continuation. For larger drawups, we find no evidence of abnormal returns, corroborating the findings of Dourado and Tabak (2014) and Saffi (2003).

5.2.3 Combined evidence on drawdowns and drawups

In the US market, the evidence supports the UIH only for drawdowns and drawups of magnitude between $2\sigma$ and $3\sigma$. Tail events seem to support the underreaction hypothesis, which predicts return continuation after large price variations. The information embedded in large consecutive price variations is not immediately incorporated into prices, or it may be positively correlated with following new information.

For the US indexes, our results are in line with those of Nam et al. (2006) and Bali et al. (2008). They document an asymmetry in the effects following large negative and positive returns. Both authors find that negative returns tend to revert more quickly than positive ones. However, unlike Bali et al. (2008), we see that abnormal returns after drawdowns of magnitude equal to or higher than $3\sigma$ support the underreaction hypothesis, so our findings...
suggest that short-term reversals tend to occur mostly after lower-magnitude drawdowns.

Table 8 summarizes the results for each stock market index. EMH is supported by estimates without statistical significance. Overreaction is supported by estimates showing reversal patterns. The underreaction hypothesis, on the other hand, is supported by estimates showing return continuation. The UIH is supported by evidence of significant positive return subsequent to large drawdowns and drawups.

Atasanova and Hudson (2008), Hudson et al. (2001), and Mazouz et al. (2009) also document asymmetries related to the size of large price changes used as triggers to observe following returns. Here, as mentioned previously, we observe these asymmetries only in the case of drawdowns in the US stock market indexes, supporting the overreaction hypothesis for events of magnitude between $2\sigma$ and $3\sigma$ and the underreaction hypothesis for larger-magnitude events.

5.2.4 Longer-duration effects

We also estimate abnormal results following large drawdowns and drawups with durations equal to or greater than 3 business days. We want to discover whether this time-dependent behavior of consecutive negative or positive returns for longer-duration periods may influence the pattern of abnormal returns observed after these events. As a whole, we cannot find any difference from patterns observed in the largest sample, with drawdowns and drawups of all durations. US indexes tend to provide evidence supporting the same hypothesis as mentioned above. The HSI and IBOVESPA, for instance, also show significant negative estimates for the 10 business days following drawdowns in both samples with all durations and durations higher than 2 business days, for events with magnitude equal to or higher than $3\sigma$ of daily series returns. We also observe no significant differences in drawups’ estimates.

5.2.5 Testing for abnormal returns on end dates

We use the same dummy approach to test whether positive and negative returns on the day after drawdown and drawup end dates have a magnitude significantly higher than average 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 return for the first business day after the event is then tested by estimating the following regression for each index daily log return $r_t$, assuming GJR-GARCH
Table 6
GJR-GARCH estimates of abnormal returns after large drawdowns

|        | NDD | DD2 | DD3 | DD4 | DD5 | DD10 | DD21 |
|--------|-----|-----|-----|-----|-----|------|------|
| DJIA   | 698 | 0.042 | 0.039*** | 0.053** | 0.048** | 0.031*** | 0.032*** |
| SP500  | 482 | 0.095** | 0.050 | 0.032 | 0.042* | 0.022 | 0.025*** |
| NASDAQ | 242 | 0.036 | 0.034 | −0.011 | 0.002 | 0.041*** | 0.035** |
| SXSE   | 183 | −0.078 | −0.116 | −0.087* | −0.036 | −0.011 | −0.044*** |
| FTSE   | 228 | 0.042 | 0.020 | −0.011 | 0.004 | 0.021 | 0.008 |
| HSI    | 229 | −0.032 | −0.190*** | −0.123 | −0.052 | −0.039 | 0.009 |
| IBOVESPA | 132 | 0.120 | 0.170 | 0.161* | 0.160** | 0.067 | 0.027* |
| MEXBOL | 118 | 0.076 | 0.111* | 0.077 | 0.128* | 0.054* | 0.030* |
| JCI    | 129 | 0.266 | 0.058 | 0.073 | 0.068 | −0.017* | 0.032 |
| KOSPI  | 235 | −0.029 | −0.100*** | −0.097 | −0.065 | −0.010 | −0.022 |

|        | NDD | DD2 | DD3 | DD4 | DD5 | DD10 | DD21 |
|--------|-----|-----|-----|-----|-----|------|------|
| DIA    | 708 | −0.214*** | −0.160*** | −0.131*** | −0.087*** | −0.050*** | −0.015* |
| SP500  | 537 | −0.058 | −0.063 | −0.040 | −0.031*** | −0.009 | −0.001 |
| NASDAQ | 305 | 0.097 | 0.002 | −0.019 | −0.028 | −0.043*** | −0.023 |
| SXSE   | 192 | −0.056 | −0.045 | −0.006 | 0.021 | −0.002 | 0.029 |
| FTSE   | 196 | 0.101 | 0.063 | 0.019 | 0.013 | −0.021 | 0.034 |
| HSI    | 256 | −0.455 | −0.291** | −0.161* | −0.096 | −0.119*** | −0.054 |
| IBOVESPA | 113 | −0.142 | −0.028 | 0.065 | 0.119 | −0.176*** | −0.035 |
| MEXBOL | 151 | 0.111 | 0.039 | −0.027 | −0.054 | 0.006 | 0.031 |
| JCI    | 162 | 0.420*** | 0.269 | 0.181** | 0.135* | 0.055 | 0.003 |
| KOSPI  | 273 | 0.011 | −0.050 | 0.015 | 0.078 | 0.007 | 0.010 |

*, ** and *** denote 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 ranging from the second to the N-th business day after drawdown end date. Large drawdowns are represented by magnitude between 2 and 3 standard deviations of the daily series returns (top) and magnitude higher than or equal to 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 following White (1982).
Predictability of stock market indexes

|       | NDD | DD2 | DD3 | DD4 | DD5 | DD10 | DD21 |
|-------|-----|-----|-----|-----|-----|------|------|
| 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 | 0.905 | 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 |
| SXSE  | 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 |
|       | 0.594 | 0.322 | 0.995 | 0.777 | 0.998 | 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 |

|       | NDD | DD2 | DD3 | DD4 | DD5 | DD10 | DD21 |
|-------|-----|-----|-----|-----|-----|------|------|
| DIA   | 756 | 0.158*** | 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 | 0.451 | 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 |
| SXSE  | 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 |

*, ** and *** denote 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 ranging from the second to the N-th business day after drawup end date. Large drawdowns are represented by magnitude between 2 and 3 standard deviations of the daily series returns (top) and magnitude higher than or equal to 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 following White (1982).
### Table 8
Summary of estimation results

| Drawdowns (2 to 3 σ) | Effic. Market | Overreact. | Underreact. | Drawups (2 to 3 σ) | Effic. Market | Overreact. | Underreact. | UIH |
|----------------------|---------------|------------|-------------|---------------------|---------------|------------|-------------|-----|
| DJIA                 | *             | *          |             |                     |               |            |             |     |
| SP500                | *             | *          |             |                     |               |            |             |     |
| NASDAQ               | *             | *          |             |                     |               |            |             |     |
| SXSE                 | *             | *          |             |                     |               |            |             |     |
| FTSE                 | *             |            |             |                     |               |            |             |     |
| HSI                  | *             |            |             |                     |               |            |             |     |
| IBOVESPA             | *             | *          |             |                     |               |            |             |     |
| MEXBOL               | *             | *          |             |                     |               |            |             |     |
| JCI                  | *             |            |             |                     |               |            |             |     |
| KOSPI                | *             |            |             |                     |               |            |             |     |
| Drawups (≥ 3σ)       |               |            |             |                     |               |            |             |     |
| DIA                  | *             |            |             |                     |               |            |             |     |
| SP500                | *             | *          |             |                     |               |            |             |     |
| NASDAQ               | *             |            |             |                     |               |            |             |     |
| SXSE                 | *             |            |             |                     |               |            |             |     |
| FTSE                 | *             |            |             |                     |               |            |             |     |
| HSI                  | *             |            |             |                     |               |            |             |     |
| IBOVESPA             | *             | *          |             |                     |               |            |             |     |
| MEXBOL               | *             |            |             |                     |               |            |             |     |
| JCI                  | *             |            |             |                     |               |            |             |     |
| KOSPI                | *             |            |             |                     |               |            |             |     |

* indicates supporting evidence from regression estimates for at least one time horizon following drawdowns or drawups. Efficient market hypothesis means no abnormal results. Overreaction means return reversals. Underreaction means return continuation after large drawdowns or drawups. The uncertain information hypothesis (UIH) is supported by the evidence when positive abnormal returns are observed after both large drawdowns and drawups.

Innovations as in eq. (3):

$$\log r_t = \alpha + \phi_{neg}D_{t, neg} + \phi_1 D_{t, 1} + \varepsilon_t.$$  \hspace{1cm} (4)

Most indexes present abnormal returns on the business day immediately after the end date of drawdowns and drawups, showing that daily positive and negative returns after both events, respectively, have magnitudes statistically higher than average returns. All estimates are positive, showing that end-date positive returns after drawdowns are higher than average positive returns, and also that end-date negative returns after drawups are lower in severity than average negative returns.

For events of larger severity (equal to or greater than 3σ), end dates of drawdowns present statistically significant abnormal returns for every index in the sample. Only the S&P500, NASDAQ, HSI, and KOSPI produce significant results for returns on drawup end dates. For those four indexes, however, we observe that the S&P500, HSI, and KOSPI show negative estimates, evidence of asymmetric behavior depending on the severity of the drawups.
6. Conclusion

In this study, we have investigated short-term abnormal returns in ten stock market indexes following large price variations. We propose a novel approach and use drawdowns and drawups as event triggers. Since these measures are not computed within a fixed time horizon, they are flexible enough to capture time-dependent subordinate processes (local dependence) that could drive 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 end date. 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). This leads to higher estimation efficiency and avoids invalid inferences due to volatility clustering close to event dates.

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 the estimates. Results also provide stronger support for the underreaction hypothesis than for overreaction, with return continuations more prevalent than reversals. Evidence for the UIH is present in some markets, mainly after events of lower magnitude. Since the UIH is an explanation based on market rationality, it seems natural to find evidence for behavioral bias explanations when drawdowns and drawups have greater magnitude.

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