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Inadequate Stock Price Reactions; Evidence from Prague Stock Exchange*

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Abstract

The paper examines how effectively a price-generating information is incorporated into the stock price. The research is dedicated to the fourteen main stocks on the Prague Stock Exchange. The investigated period was November 2012 - December 2018. The research applies a test for identifying significant price-related information, a so-called swap variance test. We analyse a price response to such information shocks. The results include both positive and negative shocks, where the positive ones are more frequent. A further exploration confirmed the existence of short-term and mid-term underreaction in the case of positive news and short term underreaction in the case of negative news. The evidence of abnormal returns identified the presence of an information inefficiency on the investigated market. The inefficiency related to negative information shocks arrives much earlier, but also lasts only for a couple of days. On the other hand, our results show that positive information shocks are more pervasive according to a portfolio holding period. We deduct from the results that investors perceive losses and gains differently and thus behave differently following the unexpected stock related news. In overall, the investors act more precise when the stock price tumbles.

1. Introduction

Since the very beginning, stock markets have been exposed to the interest of both investors and the scientific community. The subjects of interest were mainly the prices of assets. The knowledge in the existing financial theory was based on the neoclassical economic theory. According to its belief investors on a financial market should act strictly rationally. The financial theory was thus based on a considerable simplification, and the applied normative models did not take psychological factors into account. However, over time the need to explain certain market anomalies appeared. The attention of financial scientists gradually turned to behavioral finance. The trend also involved the discussion focused on the efficient market hypothesis. As it was, among other things, unable to satisfactorily investigate the problem of an inadequate reaction to new information in the process of price creation.

We consider jumps in the equity market as large infrequent changes in stock

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prices. These jumps can be used as a proxy for unexpected investment news, which influences a significant stock price movement. In the case of expected investment news, the stock price should contain no jumps, because the market participants had already incorporated such information into the stock price. An advantage of the presented jump detection methodology using jumps as a proxy for newly released unexpected information is undoubtedly its complexity. Literature which analyses only news releases of only certain events, i.e. Alwathnani et al. (2017) or Vega (2006), cannot provide explanations for systematic inadequate reactions of investors to a wide range of unexpected news. Such literature is also restricted to publicly announced events. The results of our analysis can contribute to the knowledge concerning efficient market hypothesis (EHM) or behavioral effects of the investors not only in the Czech equity market. According to the EHM, an informationally efficient market should immediately react to new unexpected information with an appropriate jump. Around these jumps, it should not be possible to earn abnormal returns. Otherwise, the market is informationally inefficient. The explanation of this phenomenon can be provided by the classical financial theory or by behavioral finance.

Our paper focuses on investigating inadequate price responses on the Prague Stock Exchange (PSE). In our research we employe the swap variance methodology following Jiang and Oomen (2008). When the price jump is identified, the price response pursuant adequate course response, underreaction or overreaction is investigated. Then, according to Jiang and Zhu (2017), we create portfolios and monitor the potential occurrence of abnormal returns. Our contribution lies in the unprecedented application of the methodology on the PSE to identify inadequate price developments. The topic follows modern trends in finance theory.

To our knowledge, there is no evidence of similarly focused research examining the capital market in the Czech Republic. Our research brings interesting results which can be used by practitioners. Nonetheless, the contribution is beneficial primarily to the scientific community dedicated to financial markets. The results of our article can be compared with some research on the developed markets or some emerging markets, for instance with Farag (2015) or Piccoli (2017).

2. Literature Review

The research interest of the paper is the capital market information efficiency. The problematics is inseparably linked to Eugen F. Fama, who put the price development process at the forefront of interest (Fama, 1965). He argues that the prices of assets on the capital markets follow a random walk process. The intrinsic value of a stock is continuously reflected in the market price of the stock. Eventual jumps in price do not reverse the theory, because jumps are caused by new relevant information that has an impact on the intrinsic value. Fama (1970) identifies three forms of market efficiency; the weak, semi-strong and strong forms. In the real world, capital markets are able to achieve at the most the weak form of market efficiency (Malkiel, 2011). It is particularly true of highly liquid and developed markets.

There are many scientific papers dedicated to testing market efficiency on developed markets. Some of the researchers were exploring price responses to information incentives. One of the initial work investigated the impact of publishing a particular report on stock price (Niederhoffer, 1971). Cutler et al. (1988) placed his research in the opposite direction. He first identified abnormal price movement and subsequently traced the relevant information. Nonetheless, both studies stated that the releasing of information is insignificant as an indicator which can explain a change in the price of a stock. Adopting Niederhoffer’s methodology, Chan (2003) analysed inadequate and exaggerated stock price responses using Dow Jones Interactive Publications Library. In the article, he distinguished the behavior of price development after price shocks with news events and no news motivated price shocks. Stock price momentum after news motivated shock was more robust than no news motivated price shocks, especially in case of reaction to bad news. Probably the most extensive analysis in this area based on the information from Down Jones News Archive was developed by Tetloc (2010) which is consistent with the asymmetric information model. As stated by Jounlin et al. (2008), an impulse for a price jump can be far more complicated than just a newspaper report. It leads to using more complex methods. Jiang and Zhu (2017) use Swap variance approach to detect jumps on the New York Stock Exchange (hereinafter as NYSE), which serves as a proxy for unexpected information shocks. They found evidence of a short-term underreaction to unexpected news. Another information-based approach uses case studies to examine price movements. Here, however, the attention is focused on a specific event directly associated with the investigated company. Typically, it is a disclosure of financial statements. The research is mostly associated with the so-called post-earning announcement drift, initially proposed by Ball and Brown (1968). Foster et al. (1984) investigated the performance of portfolios consisting of stocks with unexpected earnings changes. A gradual decline in price development has been demonstrated, considered as a momentum effect, referred to as post-earnings announcement drift. This area of research was also added to by Bernard and Thomas (1990). The authors concluded that there was a delayed market price reaction to the published information. Hirshleifer and Teoh (2003) and Hirshleifer et al. (2011) see the main reason for gradual price adjustment in the limited attention of investors. Alwathnani et al. (2017) confirmed a statistical significance of inadequate price responses to unexpected reports in published financial statements.

To a significantly lesser extent, researchers tested market efficiency in marginal markets with low liquidity. Some articles included PSE as well, e.g. Worthington and Higgs (2003) test sixteen developed and 4 emerging markets (including PSE) for random walks and weak-form market efficiency using tests of serial dependences, unit root tests and multiple variance ratio tests. Nor did they prove a weak form of the market efficiency on emerging markets (excluding the Hungarian market due to some specific issues). Hájek (2007) achieved similar results considering PSE and daily data using a simple test of linear dependences – variance ratio test. Although, Phiri (2015) found mixed results of the weak-form market efficiency of the South African market as he applied linear and non-linear unit root tests. Furthermore, Gozbasi et al. (2014) applied a similar nonlinear unit root test to re-examine Turkish stock market efficiency, proving the weak-form efficiency. Kristoufek and Vosvrda (2013) ranked 41 stock indices from all over the world according to efficiency index based on Hurst exponent and fractal dimension. The Czech’s PX reached the first, relatively the most efficient, quartile.

With a focus on literature, which examines especially behaviour after large stock price movements, the authors mostly analyse a single market. There are two general behaviours depicting market inefficiencies following a significant stock price change, namely contrarian and momentum behaviour. The contrarian behaviour suggests reversals in stock price development and the momentum behaviour presumes the stock price development in the same direction as the sudden large stock price change. The contrarian behaviour is in line with an overreaction hypothesis as a stock price firstly exceeds the intrinsic value. Similarly, the momentum represents an underreaction to the initial price impulse. For example, Farag (2015) and Boubaker et al. (2015) analyse the overreaction hypothesis due to some specific events on the Egyptian stock exchange over the period 1999-2010. The results rules in favour of the contrarian behaviour, so the large stock price movements are followed by the price reversals. Contrarian behaviour after one-day large price decreases is also supported by Angelovska (2016), which examines cumulative abnormal returns of all 10 stocks listed on the MBI10, the weighted stock index of the Macedonian Stock Exchange. More articles considering a wide range of emerging markets points out the overreaction phenomenon, or contrarian behaviour, e.g. Plastun et al. (2018) – Ukrainian stock market, Piccoli et al. (2017) – Brazilian stock market and Stefanescu et al. (2012) – Bucharest stock market. Furthermore, Cakici et al. (2013) examine value and momentum effect in 18 emerging stock markets divided into Asia, Latin America and Eastern Europe regions. Strong evidence of the momentum effect is found for all emerging markets but Eastern Europe.

In general, it seems that after large changes, the stock prices are predictable on the developed markets as well as on the emerging markets. Despite Griffin et al. (2010), who argue that emerging markets are just as efficient as developed markets, prevalent literature considers developed markets as more efficient than the latter. Moreover, the literature on the emerging markets suggests that the contrarian or overreaction hypothesis is prevalent. Unfortunately, due to the vast diversity of research approaches, model specifications, geographic locations and periods, we are not able to draw unambiguous results about market efficiency or inadequate reactions to large stock price movements on Czech stock market. The assumptions are in line with the literature review of Amini et al. (2013), who besides recommend putting more focus on the methods which locate large price changes for future researchers.

3. Methodology and Data

The most serious drawback of the most researches described above is the need to monitor particular information that is sometimes relevant and sometimes not. Therefore, to work more effectively with price anomalies, scientists' efforts were focused directly on price jumps. A jump in price should reflect a reaction to new/unexpected information. Barndorff-Nielsen and Shephard (2004, 2006) employed the so-called bipower variation test to identify price jumps. The testing of price jumps was further developed by Jiang and Oomen (2008). The methodology of Swap variance instead of bipower variance was successfully applied. Later, Jiang and Zhu (2017) investigated data from NYSE with the Swap variance jump test methodology.

In our research, we focused on sudden changes in prices. We assume that a jump in price is caused by significant information that usually comes unexpectedly. The development in asset prices or more exactly the asset returns could be formally described as follows:

$$dlnS_t = \alpha_t dt + \sqrt{V_t}dW_t + J_t dq_t \tag{1}$$

S_t is asset price, α_t is the instantaneous drift, V_t is instantaneous variance with no jump, J_t is a random variable and in the equation represents jumps in the asset price, W_t is a standard Brownian motion, q_t is a counting process with finite instantaneous intensity λ_t (Jiang and Oomen, 2008).

Employing Ito´s Lemma on (1) we obtain:

$$\frac{dS_t}{S_t} = \left(\alpha_t + \frac{1}{2}V_t\right) dt + \sqrt{V_t}dW_t + (expJ_t - 1)dq_t \tag{2}$$

If we combine both (1) and (2) and apply integration over time, the result will gain:

$$2\int_0^T \left[\frac{dS_t}{S_t} - dlnS_t\right] = V_{(0,T)} + 2\int_0^T (expJ_t - J_t - 1)\, dq_t \tag{3}$$

Here, $V_{(0,T)}$ is integrated variance so it can be expressed as $V_{(0,T)} = \int_0^T V_t dt$.

The above-given equation provides an essential tool for further jump tests. The term $V_{(0,T)}$ represents an integrated variance that describes only a continuous part of the realised variance (RV), which is defined as

$$RV_N = \sum_{i=1}^{N} r_i^2, \tag{4}$$

due to the fact, that the realised variance converges to $RV_N = V_{(0,1)} + \int_0^1 J_t^2\, dq_t$ for $N \to \infty$ (Jacod, 2017).

If the continuous part on the left side of equation (3) is transformed to a discrete form, the formula of Swap variance (SwV) with the step of 1/N on the interval [0,1] could be expressed as follows:

$$SwV_N = 2\sum_{i=1}^{N}(R_i - r_i) \tag{5}$$

The notation introduced in (Jiang and Oomen 2008) for the discrete return and for the continuous return $r_i=\ln(S_{i/N})-\ln(S_{(i-1)/N})$ is respected here.

To identify price jumps we can subtract RV_N from the left side of the equation (3) and we obtain a tool for detecting jump events because the following must apply:

$$\lim_{N\to\infty}(SwV_N - RV_N) = \begin{cases} 0 & no\ jumps, \\ 2\int_0^1 (expJ_t - J_t - 1)dq_t - \int_0^1 J_t^2 q_t & jumps. \end{cases} \tag{6}$$

The equation is based on the replication strategy, according to (Neuberger, 1994). In the case of the continuous price process, hedging could eliminate all the risk of the integrated variance. Nevertheless, in the case of jump events in the price, a stochastic unhedged error will be present in the replication strategy. The lack of the hedging strategy could be described in the following expression $2\int_0^1 \left(\frac{1}{S_t}dS_t - dlnS_t\right)$

(Jiang, Oomen 2008). Thus, to identify the jump, cumulative errors of a replication strategy could be applied over an observed time period.

We employ the jump test statistic methodology to identify jumps (Jiang and Oomen, 2008). The authors developed three statistics tests. To identify jumps in our research, we apply the ratio test with the null hypothesis of no jumps for $t \in [0,1]$. We use the ratio test because it is found to have the best finite sample properties:

$$\frac{V_{(0,1)}N}{\sqrt{\Omega_{SwV}}}\left(1-\frac{RV_N}{SwV_N}\right)\xrightarrow{d}\aleph(0,1). \tag{7}$$

According to Jiang and Oomen (2008), $\Omega_{SwV}=\frac{1}{9}\mu_6 X_{(0,1)}$, $X_{(a,b)}=\int_a^b V_u^3\,du$, $\mu_p=E(|x|^p)=2^{\mu/2}\Gamma\left[\frac{p+1}{2}\right]/\sqrt{\pi}$, where $x\sim\aleph(0,1)$. Since $V_{(0,1)}$ and $X_{(0,1)}$ are latent quantities, we have to use feasible versions of the SwV test. Barndorff-Nielsen et al. (2005) and Barndorff-Nielsen et al. (2006) show that BPV_N is a consistent estimator of $V_{(0,1)}$, whereas multi-power variation $\hat{\Omega}_{SwV}^{(p)}$ is a consistent estimator of Ω_{SwV}.

$$BPV_N=\frac{1}{\mu_1^2}\sum_{i=1}^{N}|r_i||r_{i+1}| \tag{8}$$

$$\hat{\Omega}_{SwV}^{(p)}=\frac{1}{9}\mu_6\frac{N^3\mu_{6/p}^{-P}}{N-p+1}\sum_{i=0}^{N-p}\prod_{k=1}^{p}|r_{i+k}|^{6/p} \tag{9}$$

It is recommended to use $\hat{\Omega}_{SwV}^{(4)}$ or $\hat{\Omega}_{SwV}^{(6)}$ (Jiang and Oomen, 2008). We have chosen the former option in our article.

4. Data

Our stock sample includes data of 14 common stocks, see Table 1, which are listed (or had been listed in the recent past, i.e. FOREG, UNIPE) on the PSE and which are included in PX index. Abbreviations used in this work correspond to the PSE methodology. We have omitted stocks with liquidity problems, i.e. TMR, VGP.

Table 1 Descriptive Statistics of the Stocks in Our Sample (in %, Excluding Skewness and Kurtosis)

	n	*mean*	*sd*	*med*	*trim*	*mad*	*min*	*max*	*skew*	*kurtosis*	*se*
CETV	1573	0.04	3.21	0.00	-0.01	1.69	-50.65	61.60	1.836	126.220	0.081
CEZ	1573	0.00	1.36	0.00	0.00	1.04	-8.68	6.47	-0.320	3.850	0.034
RBAG	1573	0.04	1.81	0.00	0.05	1.44	-16.19	8.63	-0.535	6.293	0.046
FOREG	1440	0.07	1.64	0.00	0.06	0.92	-14.36	15.25	-0.080	20.757	0.043
KOFOL	789	-0.01	1.22	0.00	0.01	0.83	-8.29	4.55	-0.532	4.318	0.044
KOMB	1573	0.02	1.33	0.00	0.02	0.97	-8.29	5.42	-0.154	2.572	0.033
MONET	677	0.02	1.11	0.00	0.04	0.76	-9.62	5.01	-1.575	14.967	0.043
TELEC	1573	0.07	1.82	0.00	0.03	0.95	-10.10	22.50	1.515	21.495	0.046
PEGAS	1573	0.05	1.07	0.00	0.02	0.72	-7.49	9.54	0.692	9.412	0.027
UNIPE	1517	0.06	1.22	0.00	0.04	0.81	-5.77	8.27	0.348	5.024	0.031
VIG	1573	-0.02	1.41	0.00	-0.02	1.13	-16.41	6.33	-1.037	12.144	0.036
TABAK	1573	0.03	0.99	0.00	0.04	0.68	-7.71	4.09	-1.044	8.806	0.025
STOCK	1339	0.01	2.09	0.00	0.00	1.26	-32.39	11.05	-4.040	64.111	0.057
AVST	151	0.12	1.81	0.00	0.15	1.71	-5.17	4.80	-0.140	0.244	0.147

The data set was obtained from the Bloomberg terminal. The sample period is from November 2012 (when the new trading system XETRA® was first implemented) to December 2018. We did not adjust daily returns to delistings (from both indices or stock markets) since we also wanted to incorporate its news releases into our analysis. Table 1 contains descriptive statistics of the data set using the *describe* function from the R {psych} library.

5. Jump Detection Procedure

We can divide the procedure into 4 steps. Let $\{r_{t_1}, r_{t_2}, \ldots, r_{t_N},\}$ be daily returns. The interval $[t_1, t_N]$ represents the width of the rolling windows in the jump detection procedure. In our paper, we use $N = 60$ with shift 20 days after completed jump detection window.

1. Take a return sample and perform a jump test. If the jump test does not reject a null hypothesis of no jumps, we shift our time sequence by 20 return observations and start from step 1. Otherwise, the jump test recognised at least one jump in the observed interval. Hence, we record the jump test statistic JS_0 and proceed to the next step.
2. Temporarily replace each r_{t_i} return, i.e. step by step, by the median of the sample and run the jump test procedure. We record the test statistic JS_i for each individually replaced return.
3. Construct the series $JS_0 - |JS_i|$ for $i = 1, \ldots, N$. We locate jumps as the highest value of $JS_0 - |JS_i|$ for all days in the sample. A direction of the jump is in line with the sign of the JS_0. Therefore, the highest value for $JS_0 - |JS_i|$ and the positive (negative) JS_0 locates positive (negative) jump in the stock returns.
4. Permanently replace the identified jump return by the sample median and start again from the first step.

By the procedure discussed above, based on (Jiang and Oomen, 2008), we exploit the analysis of the jump locations. The procedure is performed for each stock separately.

It is worth mentioning that 1/3 of detected negative jumps were caused by the dividend ex-dates. Although we cannot consider ex-dates as unexpected news, we have not dismissed these observations from our stock jump sample. Firstly, the sample would be distinctly smaller. Thus the statistical power and the test's sensitivity would diminish considerably. Secondly, the vast literature on ex-dividend anomaly that attempts to describe the stock price decline concerning the discounted dividend (from Miller and Modigliani, 1961; Frank and Jagannathan, 1998; to more recent Dupuis, 2019). Henry and Koski (2017) concluded that skilled investors, i.e. institutions, concentrate trading around dividend ex-dates earning them abnormal returns. For that reason, there might be a motivation to overreact or underreact.

6. Portfolio Construction Procedure

We form portfolios based on lagged cumulative jump returns (hereinafter as LCJR) over the past 20 days (hereinafter called as a decisive sequence) and sort stocks into portfolios with positive (Pp), negative (Pn) or zero (P0) lagged cumulative jump returns. Word lagged stands for the fact that the portfolios are created based on the past 20 days decisive sequence. A cumulative jump return means that we sum up all jump returns (positive as well as negative) in a decisive sequence at first and then we decide on the appropriate inclusion in the portfolio. The portfolios are constructed if and only if there exists at least one stock in Pp or Pn. It should be noted, that forming Pp and Pn is independent of each other. Hence, after each 20 days sequence, one of these situations must follow:

1. There is no jump in the decisive sequence. No portfolios are constructed, and we move to the next decisive sequence.
2. There is at least one stock with positive LCJR. We form portfolio Pp and related P0, and we move to the next decisive sequence.
3. There is at least one stock with negative LCJR. We form portfolio Pn and related P0, and we move to the next decisive sequence.
4. There is at least one stock with positive LCJR and at least one stock with negative LCJR. We form portfolio Pp, Pn, P0, and we move to the next decisive sequence.

Once all the portfolios are constructed, we compute its returns for each Pp, Pn and P0 over the multiple holding periods. For that purpose, we need to set weights for the stocks in the portfolios. In our article, we apply two different weighting methods:

1. Unweighted portfolio (unW) – all stocks have the same weights.
2. Relative weighted portfolio based on the weights in PX index (pxW) – stocks in the portfolio have specific weights assigned with respect to their weights in the PX index.

7. Results

The jump detection process was executed on the stock sample, which contained daily stock returns of 14 stocks in our data set. We have detected 113 jumps on the significance level of 0.01 by the jump test statistic methodology from equation (7), 65 of them were positive, and 48 were negative. The mean value of positive (negative) jump returns reached 6.81 % (-9.37 %). Considering these mean values to be daily stock returns, we can confirm jumps to be large changes in the stock prices. The median value of positive (negative) jump returns is 5.18 % (-7.32 %), which indicates more jumps below mean values mentioned above, but higher outlying observations. In absolute values, the biggest return among positive (negative) jumps is 61.60 % (-50.65 %), while the lowest return was 1.73 % (-1.62 % respectively). The lowest values document the advantage of the model for jumps detection, which can expose even these kinds of jumps. An overview of the basic characteristics is presented in Table 2.

The time frame of our daily return prices is approximately 6 years. Therefore, we can observe 1-2 jumps per stock a year on average. It corresponds with the description of jumps as infrequent changes in stock prices. However, a frequency of jumps is not distributed equally among as depicted in Table 3. In general, smaller companies seem to exhibit more jumps in stock price development. Most of the jumps were detected for FOREG (17), followed by PEGAS (14) and CETV (13). CETV also recorded the highest (61.60 %) and the lowest (-50.65 %) daily jump return.

Table 2 Overview of Basic Characteristics of Jump Returns (in %)

Positive jumps		***Negative jumps***	
Number of jumps	65	*Number of jumps*	48
Minimum	1.73 %	*Minimum*	-50.65 %
1st quartile	3.54	*1st quartile*	-9.66
Median	5.18	*Median*	-7.32
Mean	6.81	*Mean*	-9.37
3rd quartile	7.90	*3rd quartile*	-4.46
Maximum	61.60	*Maximum*	-1.62

Table 3 Overview of the Basic Characteristics of Jump Returns by Stocks (in %)

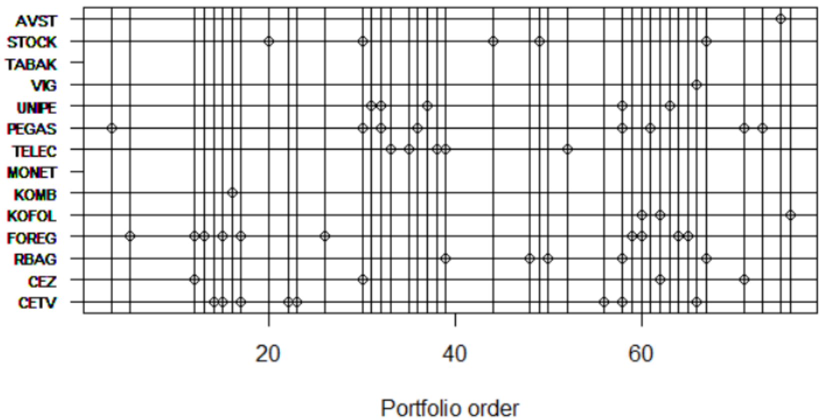
	Positive jumps						***Negative jumps***					
	n	***min***	***med***	***mean***	***max***	***sd***	***n***	***min***	***med***	***mean***	***max***	***sd***
CETV	9	4.86	10.05	14.57	61.60	17.83	4	-50.65	-19.67	-24.94	-9.79	17.78
CEZ	4	2.86	3.69	4.17	6.47	1.59	5	-8.68	-7.94	-6.83	-4.32	1.96
RBAG	5	2.58	5.18	5.75	8.63	2.30	1	-16.19	-16.19	-16.19	-16.19	NA
FOREG	14	1.73	3.68	4.30	11.39	2.64	3	-14.36	-10.68	-11.01	-8.00	3.19
KOFOL	3	2.38	6.03	5.22	7.26	2.53	3	-17.58	-3.54	-8.01	-2.91	8.29
KOMB	1	5.11	5.11	5.11	5.11	NA	4	-8.29	-5.49	-5.72	-3.59	1.95
MONET	0	NA	NA	NA	NA	NA	2	-9.62	-9.12	-9.12	-8.62	0.70
TELEC	5	5.50	8.41	11.33	22.50	6.65	7	-8.51	-6.66	-6.20	-2.76	2.06
PEGAS	8	2.21	3.34	4.63	9.54	2.80	6	-7.49	-3.13	-3.67	-1.62	2.17
UNIPE	6	3.45	4.93	5.10	6.76	1.27	1	-5.77	-5.77	-5.77	-5.77	NA
VIG	1	3.54	3.54	3.54	3.54	NA	1	-16.41	-16.41	-16.41	-16.41	NA
TABAK	1	2.86	2.86	2.86	2.86	NA	5	-7.71	-7.18	-6.24	-2.77	2.00
STOCK	7	4.22	6.95	7.17	11.05	2.41	6	-32.39	-8.32	-13.77	-2.88	12.55
AVST	1	4.32	4.32	4.32	4.32	NA	0	NA	NA	NA	NA	NA

In Figure 1, there are all portfolios which we have constructed for the analysis. Vertical lines connect all components of a particular Pp in Panel A and Pn in Panel B, while horizontal lines give information about all portfolios, in which the particular stock was included. Theoretically, we could form 77 portfolios based on the data set sample size. Although some sequences reached an empty set of jumps. Therefore, we have created, at most, 41 portfolios with positive LCJR (Pp), but only

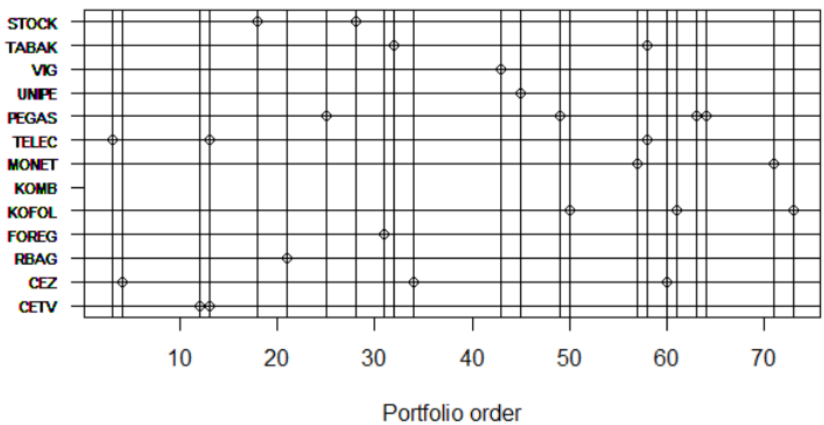
23 with negative LCJR (Pn). Considering the Pp's, PEGAS (8), FOREG (10) and CETV (8) were the most commonly contained stocks in the portfolios, while in case of Pn's, PEGAS (4) has the most inclusion. For most cases, the portfolios consisted of a single stock, especially considering the Pn portfolios.

Figure 1 Constructed Pp portfolios (Panel A) and Pn portfolios (Panel B)

Panel A:



Panel B:



Based on the prevalent results of the literature on the emerging markets, the empirical analysis was conducted to survey the contrarian behaviour on a different portfolio holding periods after 20 days portfolio decisive sequences. In case of a reaction to a positive (negative) LCJR, contrarian behaviour is similar to the overreaction to the positive (negative) unexpected news, because a price tends to return to a lower (higher) intrinsic value.

For both weighting methods, we calculate portfolio returns after each decisive sequence over the holding period, ranging from 1 to 140 days (hereinafter as 1D to

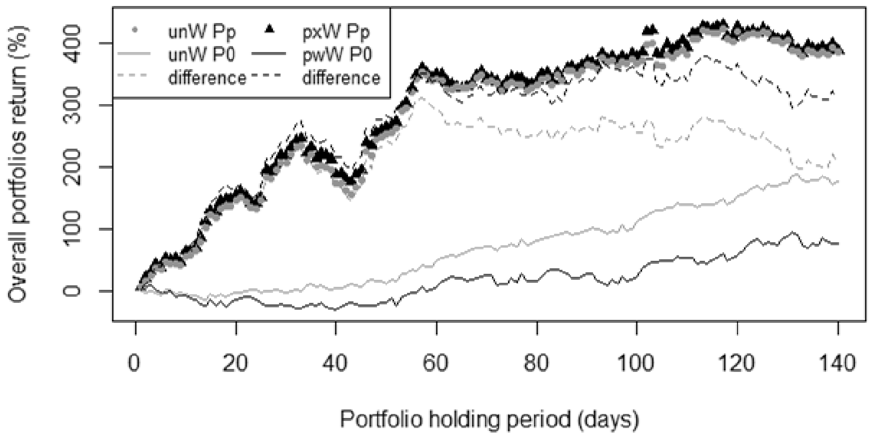
140D). As we have mentioned earlier, we formed at most 41 portfolios with LCJR for a given holding period. Therefore, e.g., for 40 days holding period, we calculate returns for 41 Pp's and related 41 P0's. We call 1 of the 41 portfolio returns a partial portfolio return. For an initial view, we construct all overall portfolio returns for Pp, Pn. The overall portfolio return is calculated as a sum of all partial portfolio returns for a given holding period.

We do not use cumulative portfolio returns to calculate the overall portfolio returns because the portfolios co-exist during the holding periods. Such a result would be hardly interpretable. Therefore, we use simple summation which calculates the overall return for all independent portfolios per each portfolio holding period. In other words, instead of reinvesting all available capital after all past partial portfolios, we always invest the same amount of capital into each partial portfolio, and we keep income and losses separate. After all partial portfolio returns per given portfolio holding period are calculated, we sum these returns to get the overall portfolio return for a given portfolio holding period. We plot overall portfolio returns for Pp in Panel A and overall portfolio returns for Pn in Panel B in Figure 2.

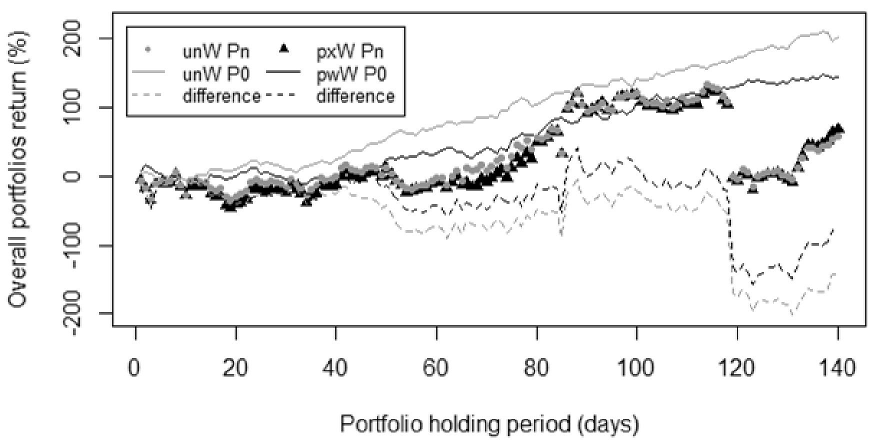
There is a substantial spread between Pp's and related P0's throughout all portfolio holding periods for both, unW and pxW portfolios. The overall portfolio returns for unW Pp are always slightly lower than pxW Pp. It suggests, that in the case of Pp's which contains at least two stocks, bigger companies (with greater weights in PX index) contribute more to the overall return than smaller companies. However, the overall portfolio returns for related unW P0's are higher than the pxW P0's since approximately five days portfolio holding period. It means that in P0's, the smaller companies outperform the bigger ones considerably. Note the different behaviour of the unW and pxW portfolios according to LCJR. Consequently, the differences between pxW Pp's and related pxW P0's are more substantial than for unW counterparties. Furthermore, it seems that the slopes for Pp's and related P0's are quite similar from about the 60-day holding period. So it is the first half of the investigated portfolio holding period, which generates the dynamics in the differences of the overall portfolio returns. Considering Pn's and related P0's overall portfolio returns, most of the time, the Pn's overall returns reach slightly lower values. The differences do not seem as significant as for Pp's. Interesting periods are 3D, 20D and the slump after 118D. In case of 3D (20D), the pxW Pn's overall portfolio return reaches -34.38% (-40.72%). Note, that it represents only 3 (20) days of holding such Pn portfolios. This result outlines a potential underreaction because the partial Pn's tends to underperform its related P0's after a negative LCJR. In other words, the price continues in the same direction as an initial negative price reaction. With the focus on 118D-119D, there is the specific drawdown in Pn which is caused by the extremely specific stock price behaviour of CETV during the period May 2013 – November 2013 when the stock price doubled its value at first to lose it back within a single trading day. We treat this particular case as an outlier and do not infer any conclusion.

Figure 2 Development of the Overall Portfolio Returns Based on the Portfolio Holding Period

Panel A



Panel B



It is necessary to point out that those calculated overall portfolio returns serve only for the comparison. It would be misleading to infer any average annual return or compound annual growth rate of the portfolios. Even though we do not use cumulative portfolio returns, we did not get rid of the portfolios co-existence problem. According to our methodology, we can hold more than one portfolio at the same time (for portfolio holding period > decisive 20-day sequence). Hence we use the overall portfolio returns of Pp's and Pn's only to compare its values with related P0's overall portfolio returns.

Table 4 Results of Testing Inadequate Stock Price Reactions

	Raw 20D Portfolio		*Raw 60D Portfolio*		*Raw 120D Portfolio*	
	unW	***pxW***	***unW***	***pxW***	***unW***	***pxW***
Median Pp	0.89%	1.23%	4.80%	4.54%	7.47%	7.49%
Median P0 (Pp)	0.41%	0.14%	1.55%	0.81%	1.92%	1.72%
Median Pn	0.75%	0.44%	2.77%	2.54%	1.42%	1.26%
Median P0 (Pn)	0.15%	-0.26%	1.31%	2.40%	4.60%	5.09%
Pp<=P0 W-stat	554	**623**	523	560	394	459
Parameter loc.	2.08%	**3.06%**	2.86%	4.08%	1.10%	4.22%
LCI (99 %)	-1.00%	**0.19%**	-1.62%	-0.28%	-6.21%	-3.37%
UCI (99 %)	Inf	**Inf**	Inf	Inf	Inf	Inf
P-value	0.056	**0.006**	0.066	0.022	0.371	0.102
Pn>=P0 W-stat	223	220	214	227	155	165
Parameter loc.	-0.85%	-0.96%	-2.03%	-1.28%	-4.58%	-4.82%
LCI (99 %)	-Inf	-Inf	-Inf	-Inf	-Inf	-Inf
UCI (99 %)	1.71%	1.87%	3.32%	3.73%	1.52%	3.58%
P-value	0.227	0.211	0.180	0.250	0.035	0.053

Notes: LCI stands for a lower conf. interval and UCI for an upper confidence interval.

The numerical values for the commonly chosen 3 portfolio holding period examples (20, 60 and 120 days) are depicted in Table 4. For both weighting methods, we compute the medians of the partial portfolios Pp and Pn which we hold for the next 20, 60 and 120 days after the decisive sequences. We also compute the same values of portfolios with no LCJR (P0) for both portfolio types, Pp and Pn, independently. The median values of each type of portfolio may outline which portfolio drives the abnormal return. Under the median section, a statistical test with the null hypothesis:

$$H_0\colon Pp \leq P0$$

is presented. Since the normality of portfolio returns is not met in most cases and the sample sizes are rather smaller, we use a nonparametric Wilcoxon signed-rank test to test the null hypothesis. The test statistics, parameter locations, p-values as well as 99 % confidence intervals are contained. We have highlighted the results of a 20 days portfolio holding period with pxW weighting method. P-value has reached 0.006, so we strictly reject H_0 on a significance level 0.01. An alternative hypothesis suggests that it is possible to reach a positive abnormal return by holding a portfolio consisted of stocks with positive LCJR during a decisive sequence for the next 20 days. When the traditionally used 0.05 significance level is applied, we reject H_0 for 60D portfolio holding period for pxW weighting method. Despite the relatively high parameter location of pxW for 120D, the confidence intervals are already much wider. So we cannot reject the null hypothesis.

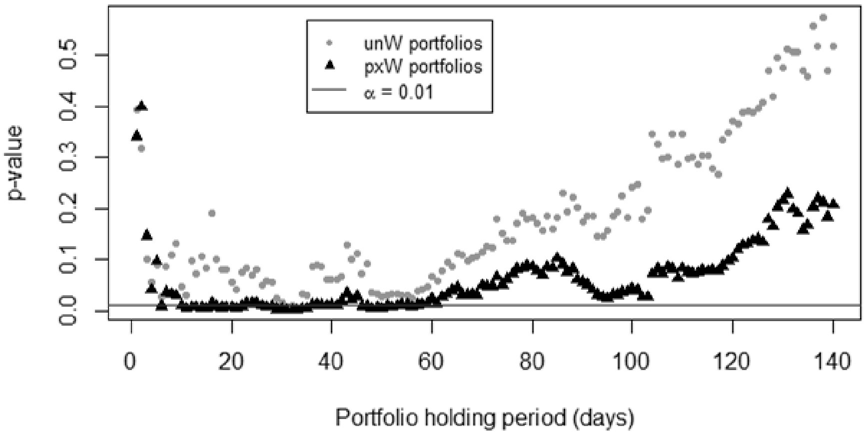
In the bottom of Table 4, we test a contrarian behaviour for portfolios with negative LCJR by setting:

$$H_0: Pn \geq P0.$$

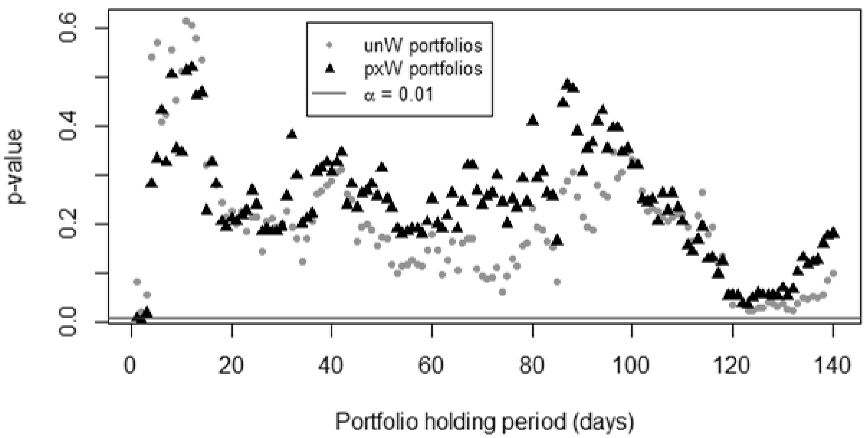
All parameter locations for 20D, 60D and 120D reach negative values. The results might indicate support for accepting the alternative hypothesis of momentum, or an underreaction to negative unexpected news, respectively. However, the confidence intervals are wide enough to contain zeros. Moreover, its upper values are relatively high (minimum: 1.87%). Thus, we do not have enough evidence to reject the null hypothesis.

Figure 3 Testing the Reactions to Positive Unexpected News

Panel A



Panel B



It seems that it is possible to earn an abnormal return within 20 and 60 days of holding created portfolios which contain stocks with positive LCJR. Thus, we are shortening the period for which the momentum effect, documented by (Jegadeesh and Titman, 1993), applies. Although we can notice high parameter values of Pp's for the 120D period as well, the Wilcoxon signed-rank test does not reject the null hypothesis. On the other hand, we did not find evidence to reject the contrarian behaviour concerning the portfolios with negative LCJR for 20D, 60D and 120D. The data outlines that contrarian behaviour does not probably describe the reactions to negative unexpected news. Looking at the confidence intervals, it rather seems, that the reactions are quite precise. Hence the reactions might be in line with the EHM.

In order to avoid any doubts regarding the chosen portfolio holding periods, we attach Figure 3. The figure contains Panel A with the p-values of the Wilcoxon signed-rank test, testing the abnormal returns of portfolios with positive LCJR for both, unW and pxW, under the null hypothesis $H_0: Pp \leq P0$ and Panel B with the Pn counterpart $H_0: Pn \geq P0$. The results for pxW portfolios in Panel A show, that for the 6D-60D portfolio holding periods, the p-values don't follow any increasing pattern and, in the most cases, we reject the null in favour of the underreaction at the 0.99 significant level. Above the 60D period, we cannot consistently reject H_0 with $\alpha = 0.01$ as the p-values rapidly increase. However, there is a drawdown in pxW around 100D period. Notice that the 100D holding period follows a 20 days decisive sequence. Altogether, it represents approximately two quarters. Thus, the drawdown may be a consequence of some semi-annual momentum regularities. Since the drawdown is specific only for pxW, we do not infer any general results and leave this particular movement out of a closer interest. The results for unW portfolios are weaker, yet it is still possible to reject H_0 on traditionally used $\alpha = 0.05$ for the similar portfolio holding period ranges. These results provide the evidence of the short-term market underreactions to positive information shocks on the Prague stock exchange, especially for the 6D-60D portfolio holding period of pwW Pp's.

Results of the Pn's abnormal return tests in Panel B show that we can reject H_0 on $\alpha = 0.01$ for 1D-3D in case of pxW portfolios, while the p-values of unW are higher. After approximately 100D, there is evident gradual decline which hits bottom for 122D portfolio holding period. The decrease is a consequence of the previously mentioned specific CETV stock price behaviour during the period of May 2013 – November 2013.

8. Conclusion

In our work, we apply the swap variance approach of the jump test methodology on the Czech equity market to test its information efficiency. We use detected jumps as a proxy for unexpected investment news that allows us to examine market reactions to all types of public and private investment news.

We provide evidence of investors' short-term and mid-term underreaction to large positive unexpected news, while the underreaction to negative information shocks news is observed only for a few days. Therefore, the investors can earn abnormal returns after the positive information shocks and shortly after the negative information shocks, which is inconsistent with the efficient market hypothesis. The results are pervasive for the different weights used to calculate portfolio returns. In fact, pxW portfolios with positive lagged cumulative jump returns show more robust results in the overall portfolio returns as well as in the statistical tests. Despite the fact, that smaller companies, i.e. stocks with lower weights in PX index, recorded more jumps than larger companies, the latter has a more significant impact of Pp’s as well as Pn’s overall portfolio returns. On the contrary, looking at the discrepancy between unW and pxW P0’s overall portfolio returns, it is intriguing that the situation is reversed as the contribution is more considerable from the smaller companies.

The underreaction to positive unexpected news is in line with the results reached by Jiang and Zhu (2017) who supported the limited investor attention hypothesis as a potential explanation on the dataset of stocks traded on the US stock exchanges. Our findings are slightly different, but also support the stock return momentum documented by Jegadeesh and Titman (1993). Although, we observed a stronger significance of abnormal gains with a shorter period of holding a portfolio. The pattern is pervasive between 10 and 60 days after the jump decisive sequence. Besides the limited investor attention hypothesis proposed by Hirshleifer and Teoh (2003) and Hirshleifer et al. (2011), we come up with another potential explanation based on the discrepant perception of the psychological value described by Kahneman and Tversky (1979) and Tversky and Kahneman (1986), who found that people perceive losses more or less twice as much as profits. Due to this so-called risk aversion, the investors remain cautious with their reaction to the positive news, whereas in the case of negative information shocks the investors immediately try to avoid further losses. It is documented by a much shorter duration of underreaction to negative information shocks, i.e. only 1-3 days. The discrepancy between the reactions to positive and negative news on the Czech equity market can be intensified by past experiences with particular stocks traded on the Prague stock exchange, i.e. NWR, ORCO, where an overwhelming slump of the prices was recorded in the past.

For further research, developing the analysis on the same market may be led by examining and adjusting the results of abnormal returns to firm characteristics or by separating the rise in the risk premium as a result of increased volatility after the sequence with located jumps.

To get more observations into jump analysis procedure, it will be necessary to seek deeper equity markets with more traded companies. With the focus on non-US stock markets, we can consider FTSE100, CAC40 or even DAX30 as suitable indices with required characteristics. On deeper markets, it might also be possible to run the jump test on high-frequency data observations. For example, 5- or 15-minutes closing prices could fit well. Another possible target for future research might be an analysis of the stock price development in the vicinity of located jumps. A much closer look at the surroundings of the jumps could help us better understand how new information is being spread. Especially the development of the stock prices before the occurrence of a jump could bring fresh findings on the insider trading phenomenon.

REFERENCES

Alwathnani AM, Dubofsky DA, Al-Zoubi HA (2017): Under-or-Overreaction: Market Responses to Announcements of Earnings Surprises. *International Review of Financial Analysis*, 52:160 – 171.

Ball R, Brown P (1968): An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, 159–178.

Bachelier L (1900): *Théorie de la spéculation. Gauthier-Villars*. Newest edition (2012), ISBN 9781400829309.

Barndorff-Nielsen OE, Shephard N (2006): Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation. *Journal of Financial Econometrics*, 4(1):1–30.

Barndorff-Nielsen OE, Shephard, N (2004): Power and Bipower Variation with Stochastic Volatility and Jumps. *Journal of Financial Econometrics*, 2 (1):1–37.

Bernard VL, Thomas JK (1990): Evidence That Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings. *Journal of Accounting and Economics*, 13(4):305 – 340.

Chan WS (2003): Stock Price Reaction to News and No-News: Drift and Reversal after Headlines. *Journal of Financial Economics*, 70(2):223 – 260.

Cutler DM, Poterba JM, Summers LH (1988): What Moves Stock Prices? *National Bureau of Economic Research Working Paper 2538*,.

Fama EF (1970): Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2):383–417.

Fama EF (1965): The Behavior of Stock-Market Prices. *The Journal of Business*, 38(1):34–105.

Farag H (2015): The Influence of Price Limits on Overreaction in Emerging Markets: Evidence from the Egyptian Stock Market. *The Quarterly Review of Economics and Finance*, 58:190 – 199.

Foster G, Olsen C, Shevlin T (1984): Earnings Releases, Anomalies, and the Behavior of Security Returns. *The Accounting Review*, 59(4):574–603.

Griffin JM, Kelly J, Nardari F (2010): Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets. *The Review of Financial Studies*, 23(8):3225–3277.

Hájek J (2007): Czech Capital Market Weak-Form Efficiency, Selected Issues. *Prague Economic Papers*, 16(4).

Huang X, Tauchen G (2005): The Relative Contribution of Jumps to Total Price Variance. *Journal of Financial Econometrics*, 3(4):456–499.

Hirshleifer D, Teoh SH (2003): Limited Attention, Information Disclosure, and Financial Reporting. *Journal of Accounting and Economics*, 36(1):337 – 386.

Jacod J (2017): Limit of Random Measures Associated with the Increments of a Brownian Semimartingale. *Journal of Financial Econometrics*, 16(4):526-569.

Jegadeesh N, Titman S (1993): Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48(1):65-91.

Jiang GJ, Oomen RC (2008): Testing for Jumps When Asset Prices Are Observed With Noise - A "Swap Variance" Approach. *Journal of Econometrics*, 144(2):352 – 370.

Jiang GJ, Zhu KX (2017): Information Shocks and Short-Term Market Underreaction. *Journal of Financial Economics*, 124(1):43 – 64.

Joulin A, Lefevre A, Grunberg D, Bouchaud JP (2008): Stock Price Jumps: News and Volume Play a Minor Role. *arXiv preprint arXiv:0803.1769*.

Kahneman D, Tversky A (1979): Prospect Theory: An Analysis of Decision Under Risk. *Econometrica*, 47:263 – 291.

Kendall MG (1953): The Analysis of Economic Time-Series-Part I: Prices. *Journal of the Royal Statistical Society*. 116(1):11–34.

Malkiel BG (2011): The Efficient-Market Hypothesis and the Financial Crisis. The Efficient-Market Hypothesis and the Financial Crisis, In *Rethinking Finance: Perspectives on the Crisis (Proceedings of a konference)*. Russel Sage Foundation.

Neuberger A (1994): The Log Contract: a New Instrument to Hedge Volatility. *Journal of Portfolio Management*, 20(2):74–80.

Niederhoffer V (1971): The Analysis of World Events and Stock Prices. *The Journal of Business*, 44(2):193–219.

Piccoli P, Chaudhury M, Souza A (2017): How Do Stocks React to Extreme Market Events? Evidence from Brazil. *Research in International Business and Finance*, 42:275 – 284.

Tetlock PC (2010): Does Public Financial News Resolve Asymmetric Information? *The Review of Financial Studies*, 23(9):3520–3557.

Tversky A, Kahneman D (1986): Rational Choice and the Framing of Decisions. *The Journal of Business*, 59(4), part 2:251 – 278.

Vega C (2006): Stock Price Reaction to Public and Private Information. *Journal of Finacial Economics*, 82(1):103 – 133.

Worthington AC, Higgs H (2003): Weak-form market efficiency in European emerging and developed stock markets. *Discussion Paper* No. 159.