Dávid Andor Rácz – Gergely Huszár

The Effects of Earnings Surprises in Quarterly Reports on S&P 500 Components

Summary: In this article, we examine with event study methodology how quarterly corporate reports affect share prices. We examine two tightly connected questions: (1) are the effects of earnings surprises in the published earnings per share (EPS) immediately incorporated into the share prices, and (2) can differences in pricing reactions between the sectors of the general stock market and the tech companies, which are more uncertainly valued be shown? According to the results in case of positive and negative EPS surprises (deviation by more than ±2% from analyst consensus) price reactions are almost complete and happen in the same direction as the deviation promptly, which however are not followed by significant abnormal returns starting from the second day after the announcement. In the group of positive news, the price reaction stemming from EPS surprises proved to be significantly higher in case of tech companies, however there is no significant difference between the two groups in case of negative surprises.[1]

Keywords: event studies; corporate announcements, market efficiency
JEL code: G14

The equilibrium price on the market of a financial product can be interpreted as the combined opinion of market participants on the value of the product, based on all the information available to them at the time. Market prices change according to the information market participants have and according to the image they form about this information; every piece of news and information that changes the perceived value of a given product on the market has an effect on supply and demand, and, as a result, on the equilibrium price of the product.

The effect that information has on prices is perhaps the most conspicuous on the stock markets. Strict disclosure regulations apply to listed companies, which means these companies are much more transparent than others. The literature on the effect of new information on share prices is extensive due to the good observability of the phenomenon. Seminal studies by *Ball and Brown* (1968), and *Fama, et al.* (1969) introduced the methodology of event study that is essentially the same as that which is in use today (MacKinlay, 1997).

The main aim of the early studies mentioned was to provide empirical confirmation for the efficient market hypothesis (Fama,

Email address: raczdavidandor@gmail.com
huszar.gergely91@gmail.com

1970). These results – and additional studies by many researchers – supported the assumption, and as a result the efficient market theory became an integral and dominant part of financial thinking. However, over time, criticism appeared in literature, mostly from experts of behavioural finance. Numerous studies that describe the connection between investor psychology and asset pricing empirically weaken the validity of the efficient market hypothesis *Hirshleifer* (2001), *Bernard and Thomas* (1989).

In the present article we examine how quarterly corporate reports affect share prices. We examine two tightly connected questions: (1) are the effects of earnings surprises in the published earnings per share (EPS) immediately incorporated into the share prices, and (2) can differences in pricing reactions between the various sectors be shown? Our hypothesis is that (1) new information triggers a change in share prices in the same direction as the sign of the surprise, but the effect is not fully reflected in prices immediately, and (2) in the tech sector the effects of surprises are more pronounced since the valuation of companies in this sector is significantly more uncertain.

The article is in four main parts. First we provide a theoretical overview, describing the factors that influence share prices. This includes the brief description of the efficient market theory and the main behaviourist theories criticising it. This is followed by the topic of the event study and the related methodology issues. The next part is the empirical part of the study. We use the components of the S&P 500 and the S&P 500 Information Technology stock indices with the highest market capitalisation, examining their corporate reports disclosed in 10 quarters. Finally, we provide a summary and describe the conclusions of our research.

FACTORS INFLUENCING SHARE PRICES

The value of any security equals the present value of its future cash flows, and in a perfect world this is the equilibrium price as well. In the case of stocks, it is the present value of future dividends.[2] As we have no comprehensive information about these future cash flows, share prices reflect the expectations of investors. However, the fundamentals, the revenue-generating ability and thus the valuation of a company change as a result of market shocks and individual shocks. This process is described by the efficient market theory.

The efficient market theory and the random walk of share prices

A market in which prices always fully reflect available information is called efficient (Fama, 1970). Share prices follow a random walk (or rather a random walk with drift since expected return can be non-zero), which implies that returns are unpredictable from past returns, and the best forecast of a return is its historical mean. On an efficient market, above-average risk-weighted returns are due to chance alone and are not sustainable in the long term. This also implies that no arbitrage opportunities exist, as prices adjust to all new information without delay (Fama, 1970; Fama, 1991; Malkiel, 2005).

Grossman and Stiglitz (1980) pointed out that costless information is a necessary condition for efficiency as it was originally defined. Otherwise it wouldn't be in the interest of investors to obtain costly information, as they would receive no compensation in a market with no arbitrage opportunities. Nevertheless, when information is inexpensive, the market price will reveal most of the informed traders' information.[3] Whenever we refer to advocates of efficiency later, we refer to this more loosely interpreted hypothesis.

We can differentiate between three forms – weak, semi-strong and strong – of market efficiency. The weak form of the theory states that future returns cannot be predicted from past data. The semi-strong form assumes that prices adjust to all publicly available information. Finally, in the strong form, it is not only publicly available, but all information that is reflected in the market price (Fama, 1970).

Criticism of efficient markets and the semi-strong form tests of efficient markets models

In addition to the effect of new information, share prices are also influenced by other factors, by several elements of psychology that *Akerlof and Shiller* (2011) call animal spirit. The theoretical framework the most closely related to our research questions is the semi-strong form tests of market efficiency. These event studies examine how share prices react when new information becomes available. On an efficient market, a surprise shock should be almost immediately and fully reflected in the market price. There is, however, extensive literature on cases when this does not happen. Possible reasons fall into two categories basically; it is either that price response is delayed, or that certain risk premiums are not included in the pricing model, so we may detect abnormal returns with it (Bernard & Thomas, 1989).

In addition to the continuation of short-term returns, Fama and *French* (1996), and Fama (1998) mention another important anomaly, the momentum after corporate reports, i.e. the share price trend, which is a series of price changes in the same direction over a longer period and which cannot be explained in the three-factor model. In addition, a number of further studies have identified different forms of pricing anomalies, including *Patell and Wolfson* (1984) and in more recent literature *Hou,* et al. (2010), *Jegadeesh and Titman* (2011), *Leippold and Lohre* (2012), *Chen, et al.* (2017), and *Maio and Philip* (2018).

Chan, et al. (1996) mentions two possible behavioural patterns that may cause post-earnings-announcement momentum. One is that due to the market's underreaction, prices adjust to new information slower. Another possibility is that 'trend-chasers' reinforce movements in stock prices even in the absence of fundamental information. Behavioural models are built on both explanations [Barberis, et al. (1998), Daniel, et al. (1998).]

Several researches mention that the effect of various cognitive biases is more significant in case of illiquid stocks (Chordia, et al., 2009; Chordia, et al., 2014), and when there is more uncertainty regarding the valuation of a company (Daniel & Titman, 1999; Hirshleifer, 2001; Kumar, 2009). The research of *Zhang* (2006) and *Francis, et al.* (2007) substantiates that price reaction to surprise news is slower in case of growth stocks where there is more uncertainty about the firm's value.

The hypotheses examined in the article

Considering the theories described in the theoretical overview, we believe that stock markets are not perfectly efficient. In spite of this, we consider the efficient market theory the starting point, which, due to the strict conditions that are necessary for methodology considerations, is not fully realised. These considerations are reflected in our hypotheses.

❶A surprise in the earnings of companies results in a change in share prices in the same direction, but the effect of the new information is detectable on the trading days after the announcement as well.

❷The effect of the surprise is more significant with stocks with more uncertain valuation, for example in the tech sector.

THE METHODOLOGY OF THE EVENT STUDY

The methodology used for the analysis of the research questions is the event study. When describing the methodology, we mostly rely on studies by *MacKinlay* (1997), *Binder* (1998), *Kothari and Warner* (2007) and *Corrado* (2011), which discuss this analysis procedure extensively. Based on this we describe the procedure of the event study, and the methodology details that are the most important for our research. In the description of the methodology, we use the notations of MacKinlay (1997).

Steps of the procedure

In finance, the question we examine is the price response of certain securities to some economic event. More precisely, we want to know if there is abnormal return as a result of the given event.

The initial task is to define the event of interest and the related event window, the period around the event over which prices will be examined. This is followed by the selection of the sample according to various selection criteria. After that we define how we will measure abnormal return. This is expressed by the following equation:

$$AR_{i\tau}=R_{i\tau}-E(R_{i\tau}|X_{\tau}) \qquad 1)$$

where $AR_{i\tau}$ is the abnormal return for security i for time period τ, $R_{i\tau}$ is the actual return, and $E(R_{i\tau}|X_{\tau})$ is the expected return. X_{τ} is the conditioning information for the expected return model, and it is determined by the available information and the asset pricing model used (MacKinlay, 1997; Kothari & Warner, 2007; Corrado, 2011).

Modelling expected returns

When calculating expected returns, we assume that the returns used for modelling are normal and are independently and identically distributed through time. According to MacKinlay (1997), the majority of event studies use two models: the constant mean return model and the market model. The constant mean return model is often considered naive in literature, as it does not differentiate between the effects of company-specific and market-specific information on share prices (Cable & Holland, 1999; Corrado, 2011). As a result, it is difficult to establish whether the abnormal returns observed are caused by the event examined or by market swings.

The market model provides a more sophisticated solution: like the CAPM-model (Capital Asset Pricing Model; Sharpe,1964; Lintner, 1965), it relates the return of any given security to the return of the market portfolio, thus reducing the variance of abnormal return and making the quantification of event effects more precise (MacKinlay, 1997; Corrado, 2011):

$$R_{it}=\alpha_i+\beta_i R_{mt}+\varepsilon_{it} \qquad 2)$$
$$\varepsilon_{it} \sim N(0,\sigma^2_{\varepsilon_i})$$

where R_{it} and R_{mt} are the period t returns on security i and the market portfolio, and α_i and β_i are the parameters to be estimated from the regression model. Coefficient β_i shows the sensitivity of security i to the market portfolio, α_i is the fitting parameter, and ε_{it} is the error term of the security over period t. We assume that the expected value of the error term is zero and has a normal distribution with a variance of $\sigma^2_{\varepsilon_i}$.

In the modelling logic we use, it is assumed that the regression coefficients are constant during the estimation period and in the event window (Binder, 1998). The actual beta of a given stock may change over time. However, examining a short-term horizon, it is unlikely that significant changes occur in risk profiles.

According to *Cable and Holland* (1999) tests indicate that the market model outperforms the CAPM. However, both models are less accurate in estimating actual abnormal returns than multifactor models (e.g. Fama and French 1996). In a large sample, bias averages out to zero, so the market model is efficient for estimating returns (Binder, 1998), and additional factors add little explanatory power (MacKinlay, 1997). Considering all the above, we use the market model in the present article for calculating normal returns.

Length of the event window and the estimation window

The length of the event window and of the estimation window is set somewhat arbitrarily, we fundamentally rely on the experiences of previous studies. The issue we examine is considered short-horizon in an event study, which means a relatively short event window is suitable for testing the hypotheses. The analysis is quite reliable when the event window is shorter than one year, and there are significantly fewer methodological problems in the course of the analysis (Kothari & Warner, 2007).

In our case, the event window must contain the date of the event and at least the following trading day so that announcements made at the end of the trading day or after the closing of the stock exchange are considered too, as in such cases the abnormal return is necessarily detectable the following day, too. This effect is especially significant when the announcement contains bad news for investors (deHaan, et al., 2015; Doyle & Magilke, 2015). In practice, the event window is usually an interval of a few weeks, symmetrically around the event date (MacKinlay, 1997).

The more reduced the size of the event window, the less likely it is that there are impacts of other confounding events pertaining to the companies (Rao & Sreejith, 2014). In our case, economically significant abnormal returns linked to corporate reports can only be expected in a period of a few days around the event. We can also see in the article by MacKinlay (1997) that a few days after the disclosure of the report, abnormal returns fluctuate around their expected value, i.e. zero. Thus a window of four weeks seems an appropriate choice.

It is important to consider that if the event window is too long as compared to the estimation window, it can significantly bias the test statistics if estimated abnormal returns are correlated. However, when the event window is 5 days long and the estimation window is 100 days long, the uncorrected test statistic is expected to exceed the corrected one by 1.6 per cent (Binder, 1998). Because of this, we use a period that is longer than MacKinlay's (1997) 120 days, for example a two-year (500 trading day) period to calculate regression coefficients, as suggested by Corrado (2011). It is important to separate the two windows in time; if we used also the return data from the event window for the regression model, the estimation of the parameters would be incorrect as it would also include the noise caused by the announcement (Boehmer, et al., 1991; MacKinlay, 1997; Binder, 1998; Kothari & Warner, 2007).

In view of the above, the timeline of the event study can be formally put as follows. The running index of returns is τ, and the stages of the study are: $\tau=0$ is the date of the event, $T_0+1 \le \tau \le T_1$ is the estimation window, and $T_1+1 \le \tau \le T_2$ is the event window. In this case $L_1=T_1-T_0$ is the length of the estimation window, and $L_2=T_2-T_1$ is the length of the event window (*see Figure 1*). A post-event window can also be defined as $T_2+1 \leq \tau \leq T_3$, with a length of $L_3=T_3-T_2$, but it is unnecessary for our research questions.

Measuring and testing abnormal returns

As expected return is modelled as the linear function of the return of the market portfolio, using equations (1) and (2) we can provide a more accurate definition of abnormal return as used in the present article:

$$AR_{i\tau}=R_{i\tau}-E(R_{i\tau}|R_{m\tau}) \quad 3)$$

where $T_1+1 \leq \tau \leq T_2$, thus τ is a period in the event window. The length of the period used for parameter estimation and the period around the event are defined, so we can start building the regression model. The least squares method is used for parameter estimation. We know the expected return calculated during modelling from (2), and substituting this to equation (3) we can calculate the abnormal returns around the event as follows:

$$AR_{i\tau}=R_{i\tau}-(\hat{\alpha}_i+\hat{\beta}_i R_{m\tau}) \quad 4)$$

where $AR_{i\tau}$ is the abnormal return of security i, and $R_{i\tau}$ and $R_{m\tau}$ are the returns of security i and the market portfolio over period τ. $\hat{\beta}_i$ is the estimated regression coefficient for the sensitivity to market return and $\hat{\alpha}_i$ is the fitting parameter.

To be able to draw statistically and economically relevant conclusions regarding the research questions, abnormal returns must be aggregated. Aggregation can be done across the elements of the sample or through time. The first part of our first hypothesis says that as a result of the announcement, share price changes in the same direction as the surprise in the EPS. This assumption can be tested if we aggregate the abnormal returns in the sample that occur when corporate reports are disclosed, based on whether the surprise is positive, negative or neutral. Based on MacKinlay (1997), Binder (1998*), Serra* (2004), and Kothari and Warner (2007), the average abnormal return in period τ $(\overline{AR}_\tau)$ is the arithmetic mean calculated from the data of the elements of the groups:

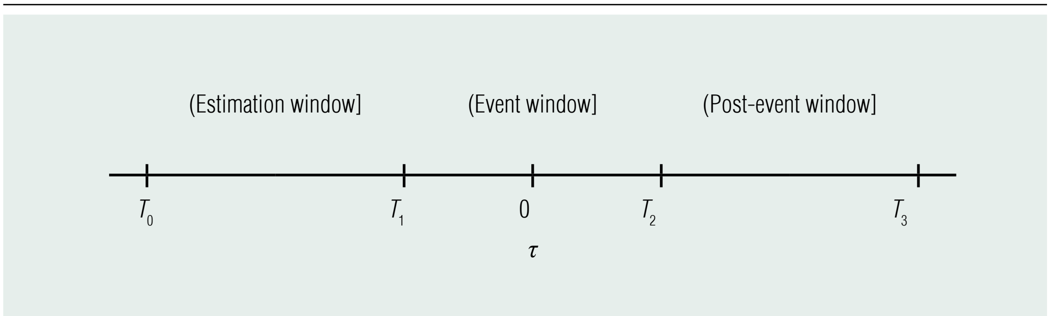
$$\overline{AR}_\tau=\sum_{i=1}^{N}\frac{AR_{i\tau}}{N} \quad 5)$$

where N is the sample size (the number of elements in the group), i.e. the number of events observed. If the value of L_1 is high, the variance is [cf. MacKinlay (1997, p. 21) equation (8)]:

$$var(\overline{AR}_\tau)=\frac{1}{N^2}\sum_{i=1}^{N}\sigma^2_{\varepsilon_i} \quad 6)$$

Figure 1

THE TIMELINE OF AN EVENT STUDY



Source: MacKinlay, 1997, p. 20

A relatively long estimation period is necessary because equation (6) is true if abnormal returns are independent through time. According to MacKinlay (1997) this is true if the size of the sample we use for estimating returns is large enough. As $\sigma^2_{\varepsilon_i}$ is not known, we need to use an estimate for this when variance is calculated. Based on MacKinlay (1997) and Binder (1998) the variance of the error term in equation (2) is a good choice for the calculation, and it can be written as follows:

$$\hat{\sigma}^2_{\varepsilon_i} = \frac{1}{L_1 - 2} \sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau})^2 \qquad 7)$$

After that the null hypothesis, i.e. that the distribution of $\overline{AR}_\tau$ is normal with an expected value of zero can be tested, thus

$$\overline{AR}_\tau \sim N[0,\ var(\overline{AR}_\tau)] \qquad 8)$$

It is important to note that to test the statistical significance of the average abnormal return we assume that in time period τ the $AR_{i\tau}$ abnormal returns of specific observations are independent and have the same distribution.

MacKinlay (1997) and Binder (1998) note that cross-sectional data are often correlated. However, this does not cause a problem for the estimation if the event windows of the specific observations do not overlap. Otherwise we cannot assume that the estimated abnormal returns of the sample elements are independent, and in this case, due to their non-zero covariance, the variance estimate is downward biased, and test statistic is upward biased. According to Binder (1998), this bias effect is negligible if the securities are chosen from different industries and the market model is used. *Rao and Sreejith* (2014) explain that when event periods are randomly dispersed, it helps avoid bias.

If we want to test both the surprise effects of corporate reports and market efficiency, we need to analyse a period longer than the interval consisting of the day of the announcement, and – in case of reports disclosed late in the day or on a non-traiding day – the following traiding day. This is described in the second part of the first hypothesis. Based on empirical results referenced earlier, we can assume that due to the surprise in the results of the companies, we could detect the momentum effect in share prices in the short term.

To be able to test this assumption, we need to aggregate abnormal returns in the event window through time. Consider an interval between τ_1 and τ_2 for which $T_1 < \tau_1 \leq \tau_2 \leq T_2$. Let cumulative abnormal return *(CAR)* of security *i* over this interval be

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \qquad 9)$$

If we perform the same for the average abnormal returns calculated for the sample and the specific elements of the groups in the sample, we get the cumulative average abnormal returns for any (τ_1, τ_2) interval of the event window.

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau \qquad 10)$$

$$var(\overline{CAR}(\tau_1, \tau_2)) = \sum_{\tau=\tau_1}^{\tau_2} var(\overline{AR}_\tau) \qquad 11)$$

where $\overline{AR}_\tau$ and $var(\overline{AR}_\tau)$ are known from equations (7) and (8) (MacKinlay, 1997; Binder, 1998).

Based on this, we can test the null hypothesis: Does the cumulative average abnormal return follow a normal distribution with an expected value of zero?

$$\overline{CAR}(\tau_1, \tau_2) \sim N[0,\ var(\overline{CAR}(\tau_1, \tau_2))] \qquad 12)$$

Or, in normalised form:

$$\theta = \frac{\overline{CAR}(\tau_1, \tau_2)}{\sqrt{var(\overline{CAR}(\tau_1, \tau_2))}} \sim N(0,1) \qquad 13)$$

With this, we have provided an overview of the main points of the methodology used. We will do the same with the second hypothesis, but there we also examine whether the results from the two samples are significantly different and whether their cumulative average abnormal returns follow a distribution with the same expected value and variance.

SHARE PRICE REACTIONS TO QUARTERLY REPORTS IN CASE OF S&P 500 STOCKS

In this chapter we present the events examined and the factors that determine sample selection, then we perform the analytical steps described in the previous chapter. The majority of the data we used for the analysis were downloaded from the Bloomberg system in November 2017, with the exception of EPS data, which were obtained from the database of Zacks Investment Research.[4]

The events observed

The sample selected for the presented event study contains certain components of the S&P 500 index. To test the first hypothesis, we examined the price movements of 30 stocks with the largest market capitalisation of the index– at the time of writing – triggered by the quarterly reports published between the first calendar quarter of 2015 and the second calendar quarter of 2017. (With the exception of Berkshire Hathaway, for which only incomplete data was available, so we used Citigroup in the sample, which had the next largest market capitalisation.) We examined 300 reports over 10 quarters altogether, so every stock selected is included in the sample as 10 separate events. We decided to use a 21-day event window for the analysis.

The sample was selected according to several selection criteria. Large companies are observed, the stocks of which are traded on liquid markets. With this, on the one hand, we avoid methodological problems like the effects of non-synchronous trading. On the other hand, the conclusions of the analysis are more reliable as the anomalies that are more frequent and intense in case of companies with smaller capitalisation and mostly with lower liquidity do not occur here.

Our second hypothesis assumes that due to the uncertainty of their valuation, tech stocks react more intensely to EPS surprises. In order to test this, another group of companies needs to be analysed, too. For this, we selected the 30 companies with the largest capitalisation from the S&P 500 Information Technology (hereinafter: S&P 500 IT) index.

There are eight companies that are included in both samples. Two stocks had to be excluded from the second sample as well, Hewlett Packard and Paypal, as not all required data were available for the observed period in the Bloomberg database. They were replaced in the sample by the next two companies with the largest capitalisation. This means the analyses to be described in the following were conducted on two samples with 300 observations each. In the second sample the stocks were not randomly selected from different industries, this must be taken into consideration when the results are interpreted.

The details of modelling

Before the hypothesis is tested, the surprise effect in the corporate results needs to be quantified. After that the parameters of the regression model used for calculating normal returns are estimated, and finally abnormal returns are calculated and adequately aggregated.

Analysis of EPS data

The surprise effect of a result announced can mostly be expressed as the percentage difference between the actual EPS (earnings per share) value over the given period and the analyst consensus before the publication of the company's report. The estimated EPS value we use is the average of the analyst estimates directly before the announcement. This indicator is compared to the actual earnings per share value on the date the announcement is made. This means the actual data does not include the reviews of the corporate results published later, as the market is not aware of those at the time of the event. In addition, one-time and extraordinary items are excluded from the actual EPS adjusted data, as the market is less sensitive to the filtered unique and extraordinary items than to earnings from the core operation.

After collecting the data of the sample elements and calculating the EPS-surprise, we followed MacKinlay (1997) and assigned the observations to one of three groups: reports with good news, bad news and neutral news. A deviation of no more than ±2 percent in the EPS as compared to analyst consensus is considered neutral news, a deviation more than that is considered good news or bad news. From the 300 elements in the sample from the S&P 500, 195 observations were assigned to the good news group, 28 to the bad news group, and 77 to the neutral news group, while in case of the S&P 500 IT this was 221, 18 and 61 elements respectively. The two histograms in *Figure 2* show frequency data. Good news happens much more frequently, its distribution is right skewed. The possible explanation for this is that analyst estimates are often too conservative and thus negative surprises are avoided. There are much more examples of extreme EPS surprise values in the sample from the S&P 500 IT index than in the sample from the S&P 500 index.

Estimating parameters and modelling returns

Actual returns are compared to values calculated with the (2) regression equation of the market model. In every case the estimation period is the interval of 500 trading days preceding the event window of the given observation. This is necessary, as over time the parameters of the model may change in case of individual stocks, too. This means that a separate estimation is made for each of the 300 observations, not just by stocks, which increases the explanatory power of the model and makes the calculation of abnormal returns more accurate. In the model, the market portfolio is the S&P 500 index for both samples.

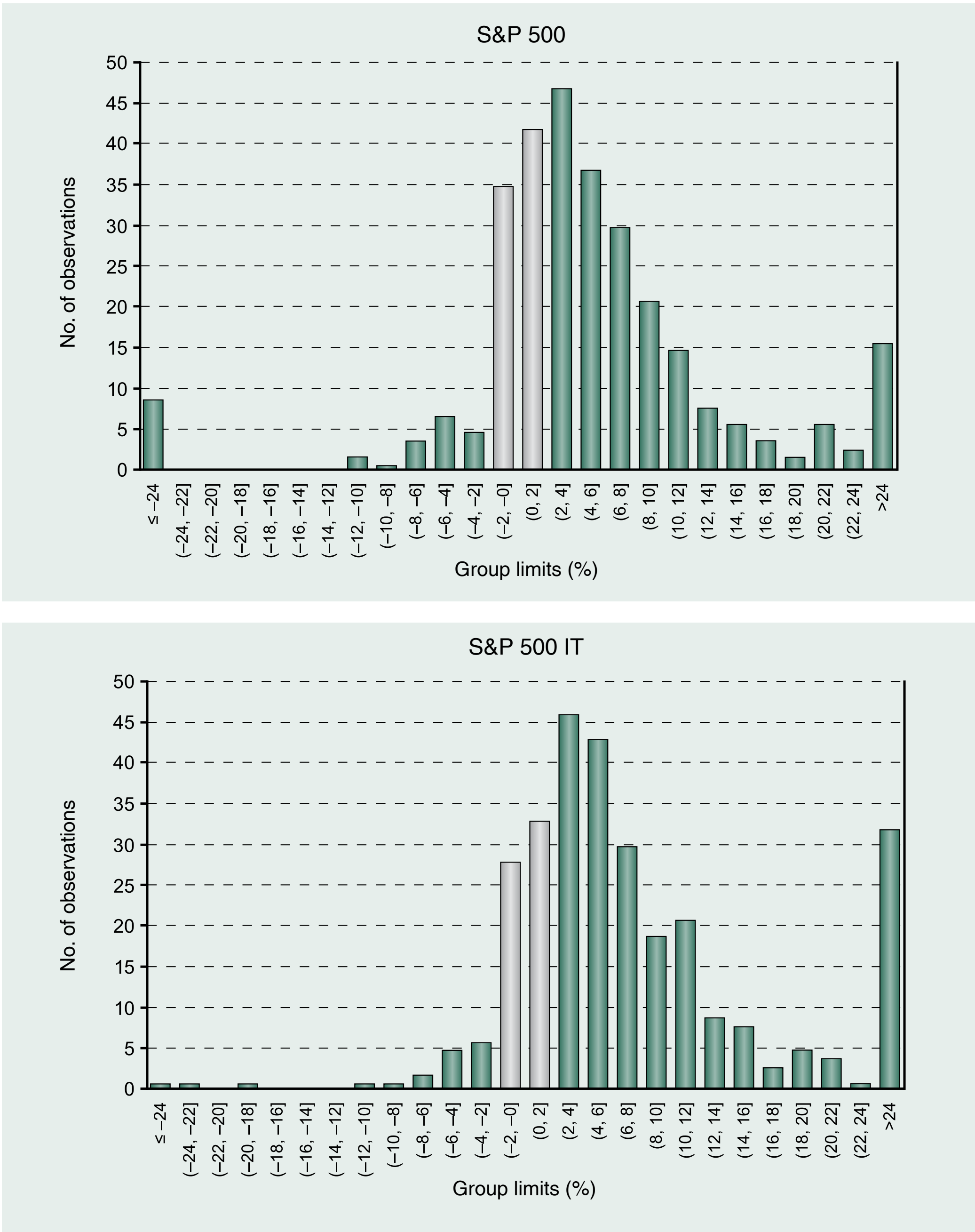
From the share price data retrieved from the Bloomberg database we calculated the daily logarithmic returns for individual stocks and for the S&P 500 index for every relevant observation period. Based on this, we estimated the parameters of the regression model. We fit 300 linear regressions on the two samples each as the $\hat{\alpha}$ and $\hat{\beta}$ parameters of each stock change over time.

In most cases α is not significantly different from zero. Due to this fact we do not use a constant term for modelling the expected returns of most of the observations, only in the equations where they were significant at 5 percent. The $\hat{\beta}$ coefficients of the specific stocks are significant at all conventional significance levels.

The R^2 indicators, which describe how the models fit, vary greatly, and a value around 50 percent can be considered high among the events observed. It is not that surprising considering that beta only shows the market

Figure 2

THE DISTRIBUTION OF FREQUENCY OF THE EPS SURPRISES IN THE OBSERVATIONS FROM THE S&P 500 AND THE S&P 500 IT INDICES (GREY = NEUTRAL NEWS)



Source: own edited, based on Bloomberg data risk of the stock, while various idiosyncratic shocks may result in a significant deviation of actual returns from values predicted with the model. *Gospodinov and Robotti* (2013) say that typically, predictive regressions of stock returns are characterised by a statistically small R^2 but possibly economically relevant.

Calculating and aggregating abnormal returns

Now we are at the most interesting part of the research, the calculation of abnormal returns, which is done according to equation (4). To test the hypotheses, the calculated data points need to be aggregated according to the chapter 'Measuring and testing abnormal returns'. It is best to examine the three groups within the sample (good news, bad news, neutral news) separately, so we calculate the average abnormal returns of the groups using equation (5) for every period of the event window. There are two ways to test whether prices move in the same direction as the direction of the surprise. One such way is to consider the cumulative abnormal return calculated for the whole event window $\overline{CAR}(-10,10)$. Assuming, however, that the information is immediately reflected in the prices or that there is no insider signal, $\overline{CAR}(0,1)$ and $\overline{CAR}(0,10)$ are also reasonable choices, where only the average abnormal returns on the trading day or days following the event are cumulated. To establish whether there is a momentum in the share prices after the announcement, it is obviously the best to shift the window, for example to $\overline{CAR}(2,10)$.

In *Table 1* and *Figure 3*, the effect of quarterly reports on share prices are clearly visible. Right until the trading day before the announcement there are minimal abnormal returns in the groups with good news and neutral news, and expected values fluctuate around zero. However, in the bad news group, data show significant cumulative abnormal returns already on the days preceding the publication of the report, with the peak on the third or fourth trading day before the announcement, followed by a correction until the announcement. As opposed to this, at the time of the announcement, the cumulative abnormal return of the two extreme groups show a surge in the direction of the surprise.

It is clear that the effect of the surprise is still strong on the trading day following the announcement, which is caused by announcements made late in the day or after trading hours. In case of the S&P 500 IT index, the range of abnormal returns is broader in all three news groups compared to the S&P 500 index. In both samples in the neutral news group, in the second phase of the event window $\overline{CAR}$ stabilises in the negative, around –1 percent, although to a lesser extent than in the bad news group and there is correction by the end of the event window.

In the group of observations with positive news, from the second trading day after the announcement, once the new information is reflected in the price, there is only a slight change in the abnormal return. In the 'bad' group, however, especially in the S&P 500 index, it seems that there is a short-term momentum in the days following the announcement.

Similarly to the $\overline{CAR}(-10,10)$ values, cumulative average abnormal returns can be analysed for any (τ_1, τ_2) interval. In the hypothesis testing, *Tables 2* and *3* show these results. Usually the extent of the abnormal returns in the various groups is relatively similar. Sometimes there is a significant decline in the neutral news group. Considering, however, that there are significantly more positive EPS surprises in both samples (*see Figure 2*), this is, besides chance, probably partly due to the fact that the sample is from the economic recovery period after the 2008 crisis.

Table 1

THE AVERAGE AND CUMULATIVE ABNORMAL RETURNS OF THE THREE SURPRISE CATEGORIES AROUND THE TIME OF THE EVENT FOR THE SAMPLES FROM THE TWO STOCK INDICES

τ	S&P 500					
	Good news		Neutral news		Bad news	
	AR %	CAR %	AR %	CAR %	AR %	CAR %
–10	0,07	0,07	–0,09	–0,09	–0,03	–0,03
–9	–0,06	0,01	0,03	–0,06	–0,18	–0,21
–8	0,10	0,11	–0,07	–0,14	–0,06	–0,27
–7	0,05	0,16	0,00	–0,14	–0,33	–0,60
–6	0,00	0,16	–0,03	–0,16	–0,10	–0,70
–5	–0,01	0,16	–0,03	–0,19	–0,15	–0,85
–4	–0,08	0,08	0,00	–0,19	–0,16	–1,02
–3	0,06	0,14	0,14	–0,05	0,62	–0,39
–2	0,06	0,19	0,11	0,06	0,10	–0,29
–1	–0,02	0,17	–0,19	–0,13	0,01	–0,28
0	0,41	0,57	–0,43	–0,56	–0,73	–1,01
1	0,70	1,27	–0,23	–0,78	–2,27	–3,28
2	0,08	1,35	0,14	–0,65	–0,43	–3,71
3	–0,05	1,31	0,07	–0,58	–0,09	–3,80
4	–0,04	1,27	–0,04	–0,62	–0,03	–3,83
5	–0,04	1,22	–0,17	–0,79	–0,15	–3,98
6	–0,10	1,13	0,20	–0,59	–0,06	–4,04
7	0,03	1,16	0,04	–0,56	–0,21	–4,26
8	0,00	1,15	0,00	–0,56	0,16	–4,10
9	0,00	1,15	0,10	–0,46	–0,08	–4,18
10	–0,07	1,08	–0,23	–0,69	0,01	–4,17

τ	S&P 500 IT					
	Good news		Neutral news		Bad news	
	AR %	CAR %	AR %	CAR %	AR %	CAR %
–10	0,02	0,02	–0,42	–0,42	–0,55	–0,55
–9	–0,01	0,01	–0,16	–0,57	–0,23	–0,78
–8	0,17	0,18	0,66	0,09	–0,46	–1,24
–7	–0,08	0,10	0,11	0,20	–0,79	–2,03
–6	0,01	0,11	–0,08	0,12	–0,06	–2,08
–5	0,11	0,22	–0,24	–0,11	–0,02	–2,11

τ	S&P 500 IT					
	Good news		Neutral news		Bad news	
	AR %	CAR %	AR %	CAR %	AR %	CAR %
–4	–0,16	0,06	–0,18	–0,30	–0,01	–2,12
–3	0,13	0,19	0,35	0,05	–0,34	–2,45
–2	0,05	0,25	–0,04	0,01	0,62	–1,83
–1	0,17	0,42	–0,25	–0,24	0,51	–1,32
0	0,37	0,79	–0,25	–0,49	0,86	–0,46
1	1,24	2,03	–0,75	–1,24	–3,91	–4,36
2	–0,01	2,01	–0,08	–1,32	0,21	–4,15
3	0,06	2,07	–0,15	–1,47	0,24	–3,92
4	–0,18	1,90	0,09	–1,38	0,52	–3,40
5	–0,07	1,83	–0,17	–1,54	–0,29	–3,68
6	–0,18	1,65	–0,30	–1,84	–1,08	–4,77
7	0,08	1,74	0,08	–1,77	0,24	–4,53
8	0,14	1,88	0,10	–1,67	0,33	–4,21
9	0,02	1,90	0,05	–1,61	–0,38	–4,59
10	–0,17	1,73	0,67	–0,95	0,72	–3,86

Source: own edited

Testing the hypotheses, interpreting the results

Figure 3 nicely shows the average abnormal returns of the groups observed. Our hypotheses are partly strengthened and partly weakened by this. To be able to establish whether what we see are really significant phenomena, the hypotheses need to be tested statistically.

Share price reactions to quarterly reports

In order to establish whether these averages are actually significantly different from zero, we conducted one-sample Student's *t*-tests. When testing the first hypothesis of the article, the tested null hypotheses and the alternative hypotheses can, in every case, be written as follows:

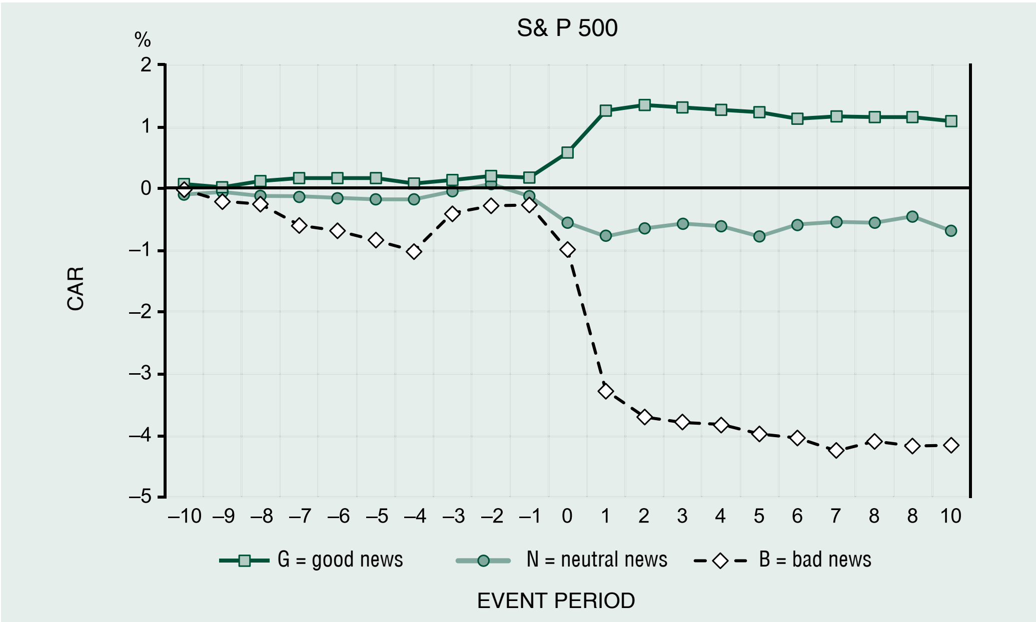
$$H_0: \theta = 0 \qquad\qquad H_1: \theta \neq 0$$

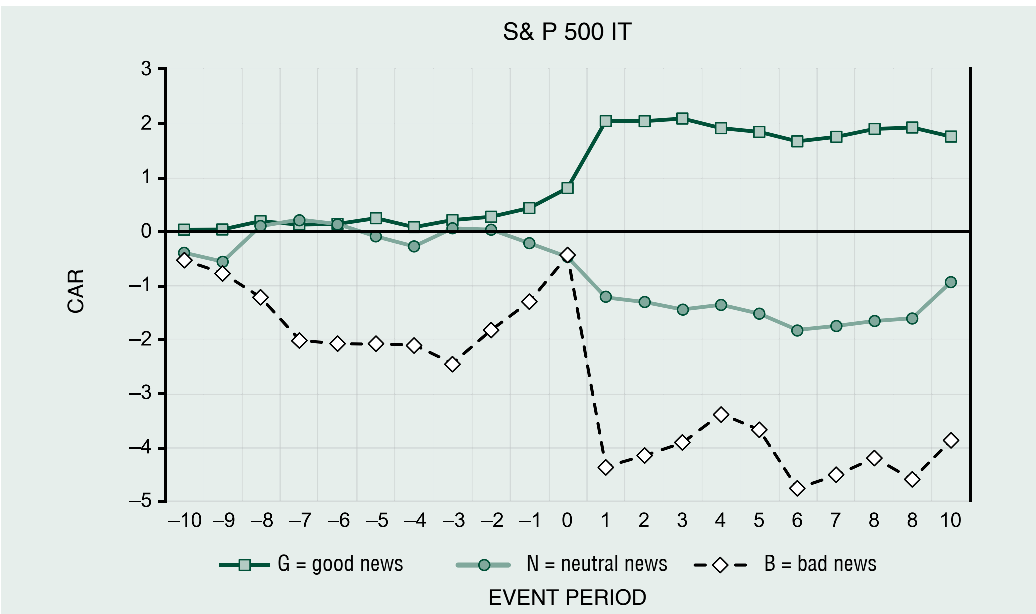
where θ, based on equation (13), is the test statistic defined as the cumulative average abnormal return measured for the interval between τ_1 and τ_2, divided by the corresponding standard deviation. The null hypothesis assumes that the value calculated this way is from standard normal distribution. Based on economic intuition we expect that the null hypothesis will be accepted in the neutral news group and will be rejected in the good news and bad news groups.

Tables 2 and *3* show the $\overline{CAR}$ values and standard deviations of the samples from the S&P 500 and the S&P 500 IT indices (is this standard deviation, which equals the square root of the variance in equation (12)), and the test statistics for various intervals of the good, bad and neutral news groups. In the chapter 'The methodology of the event study' it was mentioned that the variance of the cumulative average abnormal returns for the estimation period is estimated according to equation (6), using the error term variances calculated with equation (6). As equation (6) includes the square of the number of elements in the

Figure 3

THE CUMULATIVE ABNORMAL RETURNS OF THE THREE GROUPS AROUND THE TIME OF THE EVENT FOR THE SAMPLES FROM THE TWO STOCK INDICES (G = GOOD NEWS, N = NEUTRAL NEWS, B = BAD NEWS)





Note: On the horizontal axis: no. of days from the day of the announcement/corporate report. 0 is the day of the announcement/corporate report..

Source: own edited, based on Bloomberg data denominator, the variance is usually higher in smaller groups, which increases the probability of accepting the null hypothesis.

When describing the methodology, it was mentioned that the clustering of the event dates leads to a bias in the variance estimation, but its effect is negligible if there is no total clustering and the distribution of the observations over time is mostly random. According to the nature of the event, quarterly reports are usually published within a period of a little more than one month. Some values do not fit in this pattern, as the fiscal year at certain companies differs from the calendar year. However, this does not mean at all that there is total clustering, as the analysis covers 2.5 years and the dates of the reports are distributed over a relatively wide interval even within a quarter.

Since we test the hypotheses with two-tailed tests, $t_{0.975}$ is the critical value of the t-distribution calculated at a significance level of 5 percent and $t_{0.995}$ is the same at a significance level of 1 percent. Obviously there are differences between the groups, as the number of degrees of freedom in the tests is different in every case ($N-1$). As the distribution is symmetric, critical values on the left are the critical values on the right multiplied by –1, these are not separately indicated in the table. At a significance level of 5 percent, in the first row of *Table 2* for example, the acceptance range is the closed interval between –1.98 and 1.98.

Inspecting the values of the S&P 500, we see that as expected, the test statistics in the groups of observations with good news and bad news are very high in the whole interval of the event window (–10,10), and this value is low in case of no news reports. This means that while the null hypothesis can be rejected in the first two groups at all conventional significance levels, it is accepted in the latter. Quarterly reports have a significant effect on share prices, and the direction of the surprise unambiguously determines the sign of the cumulative average abnormal returns, too. If, however, the new information is neutral, the $\overline{CAR}$ does not significantly deviate from the expected value.

In case of positive and negative news, the $\overline{CAR}$ is even more significantly different from 0 in the 11-day (0,10) interval from the day the quarterly report is disclosed than in the whole event window, while in case of no news, it is still not significantly different from 0. In the 10-day interval (–10,–1) preceding the reports we can establish whether insider information is leaked, resulting in abnormal returns. This can be rejected in all categories. In the (0,1) interval we see significant abnormal returns with the expected direction in case of both good news and bad news. The negative $\overline{CAR}$(–0.65%) in the no news group is also significant, (although its value is materially lower than the values experienced in the bad news group). Based on the results, we don't see significant $\overline{CAR}$ values in any of the news groups in the (2,10) interval, meaning there is no significant momentum after the announcement.

The results are similar in case of the S&P 500 IT. Even though the values of the cumulative aggregated returns are somewhat higher, in this case the $\overline{CAR}$ in the negative news group is only significant at a confidence level of 95 percent. In the positive news group the null hypothesis can be unambiguously rejected for the (–10,10) interval. However, in the bad news group, the cumulative abnormal return is only different from 0 at a confidence level of 95%. Similarly to the S&P 500, in the group where there is no news in the quarterly reports, the cumulative abnormal returns are not significantly different from 0. We find basically the same if we examine the abnormal returns from the date of the announcement for the (0,10) interval.

Table 2

THE CUMULATIVE AVERAGE ABNORMAL RETURNS OF THE SAMPLE FROM THE S&P 500 INDEX, THE STANDARD DEVIATION OF THESE RETURNS, TEST STATISTICS, CRITICAL VALUES, *p*-VALUES FOR THE GOOD NEWS, BAD NEWS AND NEUTRAL NEWS GROUPS AND FOR VARIOUS TIME INTERVALS

S&P 500	τ_1, τ_2		CAR %	s %	θ	$t_{0,975}$	$t_{0,995}$	p
Good news (N = 195)	–10	10	1.08	0.35	3.13	1.97	2.60	0.0020
	0	10	0.91	0.25	3.65	1.97	2.60	0.0003
	0	1	1.10	0.11	10.34	1.97	2.60	0.0000
	2	10	–0.19	0.23	–0.83	1.97	2.60	0.4051
Neutral news (N = 77)	–10	10	–0.69	0.50	–1.39	1.99	2.64	0.1695
	0	10	–0.56	0.36	–1.55	1.99	2.64	0.1243
	0	1	–0.65	0.15	–4.26	1.99	2.64	0.0001
	2	10	0.09	0.33	0.29	1.99	2.64	0.7724
Bad news (N = 28)	–10	10	–4.17	0.95	–4.40	2.05	2.77	0.0002
	0	10	–3.89	0.69	–5.67	2.05	2.77	0.0000
	0	1	–3.00	0.29	–10.27	2.05	2.77	0.0000
	2	10	–0.89	0.62	–1.43	2.05	2.77	0.1636

Source: own edited

Table 3

THE CUMULATIVE AVERAGE ABNORMAL RETURNS OF THE SAMPLE FROM THE S&P 500 IT INDEX, THE STANDARD DEVIATION OF THESE RETURNS, TEST STATISTICS, CRITICAL VALUES, *p*-VALUES FOR THE GOOD NEWS, BAD NEWS AND NEUTRAL NEWS GROUPS AND FOR VARIOUS TIME INTERVALS

S&P 500 IT	τ_1, τ_2		CAR	s	θ	$t_{0,975}$	$t_{0,995}$	p
Good news (N = 221)	–10	10	1.73	0.42	4.15	1.97	2.60	0.0000
	0	10	1.31	0.30	4.36	1.97	2.60	0.0000
	0	1	1.61	0.13	12.54	1.97	2.60	0.0000
	2	10	–0.30	0.27	–1.09	1.97	2.60	0.2748
Neutral news (N = 61)	–10	10	–0.95	0.68	–1.39	2.00	2.66	0.1701
	0	10	–0.71	0.49	–1.44	2.00	2.66	0.1562
	0	1	–1.00	0.21	–4.76	2.00	2.66	0.0000
	2	10	0.29	0.45	0.66	2.00	2.66	0.5137
Bad news (N = 18)	–10	10	–3.86	1.41	–2.75	2.11	2.90	0.0137
	0	10	–2.54	1.02	–2.50	2.11	2.90	0.0231
	0	1	–3.04	0.43	–7.01	2.11	2.90	0.0000
	2	10	0.50	0.92	0.54	2.11	2.90	0.5931

Source: own edited

In the good news, neutral news and no news groups, there is no significant $\overline{CAR}$ in the 10-day (–10,–1) interval preceding the announcement, either. The (0,1) interval shows similar and significant results as the S&P 500, in both the good news and the bad news groups. The neutral news category, however, shows significantly negative $\overline{CAR}$ values here too (although to a much lesser extent than the bad news group). The extent of the price reaction in this index is somewhat larger in the good news category than in the S&P 500 index, and the extent of the price reaction to negative news is basically the same in both indices. The period after the quick price reaction to the corporate announcements does not show significant abnormal returns in the (2,10) interval here either, there is no trend observed.

Summing up the results presented, the analysis substantiates that the market of the stocks in the selected sample is moderately efficient. We accept the first statement of the first hypothesis: the announcement of corporate results triggers a significant and immediate price reaction in the direction of the EPS surprise. However, we reject the second statement of the hypothesis, as there is no longer a significant cumulative abnormal return in the (2,10) interval.

Differences in the effects of the EPS surprise

The second hypothesis of the article states that the cumulative average abnormal returns caused by the surprise in the tech sector are different from the values in the other sample, and in the case of tech stocks the difference from zero is larger, as the valuation of the companies in the sector is probably more uncertain.

Two-sample *t*-tests can be used to test whether the cumulative average abnormal returns in the good and bad news groups of the two samples are significantly different. [Based on Hunyadi and Vita (2008), Chapter 7]. The variances of the two samples were statistically different, so we apply the two-sample *t*-test for the cumulative abnormal returns measured in the (–10,10) interval. In this case we examine the following hypothesis pair:

$$H_0\text{: } \overline{CAR}_{SP}(-10,10) = \overline{CAR}_{SPIT}(-10,10),$$

$$H_1\text{: } \overline{CAR}_{SP}(-10,10) \neq \overline{CAR}_{SPIT}(-10,10),$$

where the lower indices denote the sample from the given stock index, and in this case we, again, compare the positive and negative EPS-report categories in pairs. In this case *t*-statistics can be calculated with the following formula:

$$t = \frac{\overline{CAR}_{SP}(-10,10) - \overline{CAR}_{SPIT}(-10,10)}{\sqrt{S_{SP}^2 / N_{SP} + S_{SPIT}^2 / N_{SPIT}}} \qquad 14)$$

where N_{SP} and N_{SPIT} are the number of elements in the examined category of the given index.

Based on *Table 4*, the *t*-statistic is –17.32 in the good news group, 2.45 in the neutral news group and –0.81 in the bad news group. The null hypothesis can be rejected at all conventional significance levels in case of the good news and the neutral news groups, which means that the cumulative average abnormal returns observed are statistically different. However, in the bad news group, the null hypothesis is accepted at all conventional significance levels, which means the cumulative returns observed are statistically the same.

This has mixed implications for the second hypothesis, as the price reaction of tech stocks is significantly higher in the good news group around the time of the quarterly reports, but in case of bad news, there is no significant difference between the two groups. The accuracy and strength of the analysis, however, may

Table 4

T-STATISTICS OF THE DIFFERENCE BETWEEN THE CUMULATIVE AVERAGE ABNORMAL RETURNS OF THE SAMPLES FROM THE S&P 500 AND THE S&P 500 IT INDICES FOR THE GOOD NEWS, BAD NEWS AND NEUTRAL NEWS GROUPS FOR THE (–10,10) INTERVAL

	t-stat	Degrees of freedom	$t_{0,975}$	$t_{0,995}$
Good news	–17,32	412,50	–1,97	1,97
Neutral news	2,45	106,48	–1,98	1,98
Bad news	–0,81	26,93	–2,06	2,06

Source: own edited

be affected by the fact that there were only 28 and 18 stocks in the two bad news groups, and probably a larger sample is necessary to explain the observed phenomenon, a sufficient number of observed stocks needs to be included in every observed group.

SUMMARY AND OUTLOOK

The research questions of the study focused on the analysis of the effects of corporate quarterly reports. For this, we analysed two samples from the S&P 500 and S&P 500 IT indices with 300 elements each. Both samples consisted of the quarterly reports, 10 each, of the 30 largest firms of the respective indices. The samples were divided into groups based on whether the surprise in the earnings per share was good news, bad news or neutral news for the market.

We accept the first statement of the first hypothesis we examined: in case of positive or negative EPS surprises, there is a quick and almost full price reaction significantly different from 0 in the same direction as the surprise. However, we reject the second statement of the hypothesis, as no effect of the surprise can be observed from day two,[5] there is no trend observed after the reports are published.

The test of the second hypothesis confirmed that the price reactions of tech stocks to EPS surprises are significantly higher in the good news group, but in case of bad news, there is no significant difference between the two groups.

The small sample size in the bad news group calls for caution in the interpretation of the results of both hypotheses, and it would be worth conducting an analysis in the future on a larger sample with sufficient number of observations in all the groups. The analytical techniques described in the article should be used for less liquid stocks and smaller markets as well. However, in addition to the issue of a sufficient number of observations in all groups, additional methodological problems would occur here. Smaller companies are probably covered less extensively by analysts, which means EPS predictions would be incomplete or one-sided, and would reflect actual market expectations to a much lesser extent.

Notes

[1] We are grateful to Péter Csóka and Miklós Pintér for their valuable comments and advice. We also thank Edina Berlinger, Anita Lovas, Kata Váradi and Ágnes Lublóy, who contributed to our work with several comments and recommendations, and we thank an anonymous reviewer for their useful remarks. Naturally, the authors are solely responsible for any errors in the article and also for the conclusions and opinions expressed. We did not rely on any external funding in the course of our research, and we do not have any interests, financial or otherwise, that could have affected our results and conclusions.

[2] For dividend patterns and the pricing of stocks see e.g. Havran et al. (2015).

[3] One example is the time when quarterly reports are disclosed: accurate information becomes available to wide audiences, which temporarily increases the liquidity of the shares (Váradi et al., 2012).

[4] Available from here: Zacks, https://www.zacks.com/stocks/ (retrieved: 01.10.2018)

[5] There are no cumulative abnormal returns significantly different from 0 on the (2,10) interval.

References

Akerlof, G. A., Shiller, R. J. (2009). *Animal Spirits. How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism.* Princeton University Press

Ball, R., Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research,* 6(2), pp. 159–178

Barberis, N., Shleifer, A., Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics,* 49(3), pp. 307–343

Bernard, V. L., Thomas, J. K. (1989). Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?. *Journal of Accounting Research,* 27., pp. 1–36

Binder, J. J. (1998). The Event Study Methodology Since 1969. *Review of Quantitative Finance and Accounting,* 11(2), pp. 111–137

Boehmer, E., Musumeci, J., Poulsen, A. B. (1991). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics,* 30(2), pp. 253–272

Cable, J., Holland, K. (1999). Modelling normal returns in event studies: a model-selection approach and pilot study. *The European Journal of Finance,* 5(4), pp. 331–341

Chan, L. K. C., Jegadeesh, N., Lakonishok, J. (1996). Momentum Strategies. *The Journal of Finance,* 51(5), pp. 1681–1713

Chan, L. K. C., Karceski, J., Lakonishok, J. (2007). Analysts' Conflict of Interest and Biases in Earnings Forecasts. *Journal of Financial and Quantitative Analysis,* 42(4), pp. 893–914

Chen, H-Y., Chou, P-H., Hsieh C-H. (2018). Persistency of the momentum effect. *European Financial Management*, 24(5), pp. 856–892

Chordia, T., Goyal, A., Sadka, G., Sadka,

R. (2009). Liquidity and the Post-Earnings-Announcement Drift. *Financial Analysts Journal,* 65(4), pp. 18–32

Chordia, T., Subrahmanyam, A., Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?. *Journal of Accounting and Economics,* 58(1), pp. 41–58

Corrado, C. J. (2011). Event studies: A methodology review. *Accounting & Finance,* 51(1), pp. 207–234

Daniel, K., Hirshleifer, D., Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance,* 53(6), pp. 1839–1885

Daniel, K., Titman, S. (1999). Market Efficiency in an Irrational World. *Financial Analysts Journal,* 55(6), pp. 28–40

Daniel, K. D., Hirshleifer, D., Subrahmanyam, A. (2001). Overconfidence, Arbitrage, and Equilibrium Asset Pricing. *The Journal of Finance,* 56(3), pp. 921–965

deHaan, E., Shevlin, T., Thornock, J. (2015). Market (in)attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics,* 60(1), pp. 36–55

Doyle, J. T., Magilke, M. J. (2015). *The Strategic Timing of Management Forecasts.* [Online] Available at: http://ssrn.com/abstract=1479867 (Retrieved on: 21 April 2016)

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

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance,* 46(5), pp. 1575–1617

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics,* 49(3), pp. 283–306

Fama, E. F., Fisher, L., Jensen, M. C., Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review,* 10(1), pp. 1–21

Fama, E. F., French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance,* 47(2), pp. 427–465

Fama, E. F., French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. *The Journal of Finance,* 51(1), pp. 55–84

Francis, J., Lafond, R., Olsson, P., Schipper, K. (2007). Information Uncertainty and Post-Earnings-Announcement-Drift. *Journal of Business Finance & Accounting,* 34(3–4), pp. 403–433

Gospodinov, N., Robotti, C. (2013). Asset Pricing Theories, Models, and Tests. In: H. K. Baker, G. Filbeck, ed. *Portfolio Theory and Management.* N.p.:Oxford University Press, pp. 46–72

Grossman, S. J., Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review,* 70(3), pp. 393–408

Havran, D., Lovas A., & Berezvai Z. (2015). *Vállalati pénzügy (SPM, SKM): Gondolkodtató és gyakorló feladatok gyűjteménye [Corporate Finance (SPM, SKM): Collection of thought provoking and practicing tasks].* Budapest: Befektetések és Vállalati Pénzügyi Tanszék Alapítványa

Hirshleifer, D. (2001). Investor psychology and asset pricing. *The Journal of Finance,* 56(4), pp. 1533–1597

Hou, K., Peng, L., Xiong, W. (2009). *A Tale of*

Two Anomalies: The Implication of Investor Attention for Price and Earnings Momentum. [Online] Available at: http://ssrn.com/abstract=976394 [Retrieved on: 26 April 2016]

Hunyadi, L., Vita, L. (2008). *Statisztika II. [Statistics 2].* Budapest: Aula

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

Kothari, S. P., Warner, J. B. (2007). Econometrics of Event Studies. In: B. E. Eckbo, ed. *Handbook of Corporate Finance. Empirical Corporate Finance.* N.p.: North Holland, pp. 3–36

Kumar, A. (2009). Hard-to-Value Stocks, Behavioral Biases, and Informed Trading. *The Journal of Financial and Quantitative Analysis,* 44(6), pp. 1375–1401

Leippold, M., Lohre, H. (2012). International price and earnings momentum. *The European Journal of Finance,* 18(6), pp. 535–573

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, 20(4), pp. 587–615

Maio, P., Philip, D. (2018). Economic activity and momentum profits: further evidence. *Journal of Banking and Finance*, 88, pp. 466–482

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature,* 35(1), pp. 13–39

Malkiel, B. G. (2005). Reflections on the Efficient Market Hypothesis: 30 Years Later. *The Financial Review,* 40(1), pp. 1–9

Patell, J. M., Wolfson, M. A. (1984). The Intraday Speed of Adjustment of Stock Prices to Earnings and Dividend Announcements. *Journal of Financial Economics,* 13(2), pp. 223–252

Rao, S. V. D. N., Sreejith, U. (2014). Event Study Methodology: A Critical Review. *The Macrotheme Review,* 3(1A), pp. 40–53

Serra, A. P. (2004). *Event Study Tests: A Brief Survey.* [Online] Available at: http://ssrn.com/abstract=1066816 [Retrieved on: 28 April 2016]

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance,* 19(3), pp. 425–442

Váradi, K., Gyarmati Á. & Lublóy Á. (2012). Virtuális árhatás a Budapesti Értéktőzsdén [Virtual price effects on the Budapest stock exchange]. *Közgazdasági Szemle,* 59(5), pp. 508–539

Zhang, X. F. (2006). Information Uncertainty and Stock Returns. *The Journal of Finance,* 41(1), pp. 105–136