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EVENT STUDY METHODOLOGY IN M&A RESEARCH*

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Abstract

Subject. The article presents the basic principles of the event research methodology, which is one of the most popular empirical tools in corporate finance, and mergers and acquisitions.

Objectives. The article introduces the main methodologies for calculating expected and abnormal returns, the main approaches for testing abnormal returns and measuring the statistical significance of the results, and it also notes the advantages and limitations of the methodology.

Methods. Based on a content analysis of the top classical works in event analysis, the main algorithm and research approaches of the method are presented. The basic concept has been expanded taking into account the results of modern work aimed at improving the methodology. The applicability of the method and its relevance were verified based on the analysis of spotlight publications for 2015–2020.

Results. The article provides a review of the latest developments in M&A research. It highlights the main modern trends in the application of the event analysis method. The methodology is shown to be easy to use, with market data used for analysis available in major financial databases. This allows for empirical research with a large sample of securities. In addition, stock prices reflect the direct expectations of investors and best reflect the value created by the event when compared to financial statement analyses that are often misstated.

Conclusions and Relevance. It is concluded that the event analysis method remains the key methodology in the field of mergers and acquisitions and is actively used by researchers. Improved econometric approaches allow for increased statistical significance and more accurate results.

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Introduction

Firstly introduced by J.C. Dolley [1] in 1933[1], event-studies have become a widely used and acknowledged empirical tool in capital market research. In the late 1960s, R. Ball and

[*] The English text is provided by the author.

[1] In his paper, J.C. Dolley (1933) examined stock price reaction to stock splits, studying changes in price at the time of the split. Based on the sample of 95 splits from 1921 to 1931, the author found that the price increased in 57 and declined in only 26 cases.

P. Brown (1968) [2] and E.F. Fama et al. (1969) [3][2] reintroduced the methodology to the broad audience and facilitated its multifold applications to the firm specific, financial and economic events. Since then, many modifications of event-studies have been developed, aiming to alter statistical assumptions and advance the design in order to challenge more specific hypotheses. Other authors addressed the practical importance of those adjustments, so S.J. Brown, J.B. Warner [4, 5] (1980, 1985) devoted their papers to the issues of using data sample at a monthly versus daily interval.

Event studies measure the effect of a particular event on the market value of a firm, using financial data. In its basic assumptions, the event study relies on rationality of the market place and effectiveness of capital markets and follows the fact that impact of an event is immediately reflected in security prices. Therefore, it allows to develop a performance measure using the security prices during a relatively short period of time, compared to other measures, like accounting measures, which require many months of observation.

"An event study is a statistical technique that estimates the stock price impact of occurrences such as mergers, earnings announcements, and so forth. The basic notion is to disentangle the effects of two types of information on stock prices – information that is specific to the firm under question (e.g. dividend announcement) and information that is likely to affect stock prices market wide (e.g. change in interest rates)" [6, p. 556].

Therefore, event study methodology allows to measure the success of transactions from the perspective of shareholder value by analyzing the unexpected, or "abnormal" returns to shareholders either in the period of the public announcement of a transaction or in a subsequent longer timeframe. As this approach relies on the assumption that share prices reflect the present value of all expected future cash flows, it is considered as future-oriented measure of success of acquisitions [7]. Moreover, event studies make it possible to yield insights into abnormal returns for shareholders of the acquirer, the target company, or a combination of both.

2. Methodological Concept

A classical event study can be divided into five steps: (i) the definition of the event and the time for which the reaction of share prices is to examine – the "event window"; (ii) the specification of a benchmark model for normal stock return behavior and identification of the estimation window; (iii) calculation of abnormal returns of a share around the event day, i.e. the difference between the existing and the expected return; (iv) design of a framework for testing abnormal returns and (v) the analysis of results and measurement of their statistical significance. These steps are discussed hereinafter in detail.

[2] R. Ball and P. Brown (1968) investigated the impact of information around the announcement of earnings, E.F. Fama, L. Fischer, M.C. Jensen, R. Roll (1969) analyzed the effects of stock splits on share price excluding the possible impact of synchronous rise of dividends. According to C.J. Corrado (2011), their success was explained by the use of *market model* in line with newly developed capital asset pricing model (CAPM) of W.F. Sharpe (1964) and use of data from newly introduced Center for Research in Security Prices (CRSP) at the University of Chicago.

- **Step (i): Definition of the event and the event window**

In case of analyzing M&A, the day of merger announcement is usually chosen as event of interest [8][3]. According to P. Dodd and J. Warner [9] (1983), the announcement date of an acquisition is the first day of public announcement. Therefore, the day the information about the transaction appears in public news (e.g. in the Wall Street Journal or another public news source) is commonly chosen as the event day or the so-called "day-0". However, as we know from the previous discussion about the market efficiency, it may be possible that the information about a future transaction becomes available to the internal market participants, making insider trading possible and affecting prices of shares. Taking this fact into consideration, the event window is usually defined larger than one day of interest. Indeed, in practice the analyzed event window often expands to several days, including at least one or more days before and after the announcement. Other studies analyze share price reaction over even larger time horizon of up to several years subsequent to the announcement, with assumption that new information can become available to shareholders and affect the merger, or new bidders can arrive changing conditions of the transaction and therefore expectations of investors. The use of such long-run studies and their analytical techniques are however controversial in the finance literature. One explanation is that for periods beyond a few months it is difficult to solely attribute abnormal share returns to the acquisition rather than to other activities of the acquirer [10][4]. Since this paper is focused on the short-run event study, the long-run event studies are not discussed further.

Overall, a definition of event-window remains still an empirical question open for discussion. The majority of reviewed studies calculated abnormal returns for the period from one trading day before until one trading day after the announcement, i.e. the [−1,1] interval, which is supposed to be the shortest event window. However, most authors used different event windows to adjust for possible information lags. The most frequently applied intervals for the event windows are [−2,2], [−5,5], [−10,10], and [−20,20] [8, 11][5].

- **Step (ii): Specification of a benchmark model for normal stock return behavior and identification of the estimation window**

The major goal of an event study is to analyze the changes in the returns for firms experiencing a specific event. An evaluation of the impact of the event is usually done through measuring of abnormal returns. In its simplest form, an event study compares

[3] G. Andrade, M. Mitchell, E. Stafford (2001) extend this definition and state that the entire wealth effect of a merger will be completely incorporated in stock prices by the time „uncertainty is resolved“ – by merger completion. Therefore, they consider both events – the day of announcement and the day of completion of merger and use two types of event widows – the three days surrounding the event and a longer event period beginning 20 days before the announcement and ending at the close of merger.

[4] S.P. Kothari, J.B. Warner (1997) claim that long-horizon tests are especially sensitive to the joint-test problem, and their usage requires "extreme caution" (p. 301). This point of view is also supported by J. Lyon, B. Barber, C. Tsai (1999), who state that even using the best methods "the analysis of long-run abnormal returns is treacherous" (J. Lyon, B. Barber, C. Tsai (1999), p. 165). E.F. Fama (1998) concludes that his survey of the long-run performance literature might be nothing more than chance results. Nevertheless, the long-run event studies are quite popular and widely used in the academic literature, although requiring a sophisticated methodology.

[5] Some authors use even longer event windows, e.g. S. Spyrou, G. Siougle (2007) with 252 days before and 252 days after the announcement. However, G. Andrade, M. Mitchell, E. Stafford (2001) states that with the length of the period statistical significance becomes reduced.

the event day return R_0 with returns observed during a control period before the event, or the so-called normal returns, which are defined as expected returns, which can be achieved in the capital market without occurrence of the event. However, this model is considered to be too simple as it does not differentiate between the impact of firm-specific information and the market-wide information affecting the stock price. Therefore, in order to measure the effect of an event correctly, it is important to control for all possible factors. The ability to select the right benchmark model to analyze the normal returns is the central skill to perform the event study.

There is a number of approaches that can be applied as a benchmark model in order to calculate normal returns. Generally, they can be divided into two categories – statistical and economic. According to C.J. Corrado [12] (2011), statistical models assume that returns are distributed independently, jointly normally and similarly through the time, while economic models rely on assumptions based on investors' behavior and therefore, are not solely based on statistical assumptions. However, A.C. MacKinlay [13] (1997) underline the need to add statistical assumptions to the economic models while using them in practice. Both models are presented in the *Fig. 1*.

Statistical models are represented through two widely used approaches – the constant mean return model and the market model. The constant mean model assumes that mean return of a single security stays constant over time. Mathematically it can be expressed in the following form [4, 5][6]:

$$R_{it}=\mu_i+\zeta_{it}, \text{with } E(\zeta)=0, \operatorname{var}(\zeta_{it})=\sigma^2_{\zeta it} \quad , \qquad (1)$$

where μ_i is mean return for asset i, R_{it} is period t return on security i, ζ_{it} is the time period t disturbance term for security i, under assumption of zero expectations and variance $\sigma^2_{\zeta\, it}$.

The market model relates returns on any security to the returns of market portfolio. It assumes a linear relationship between the return of share i and the return of a market portfolio m, and a jointly normal distribution of asset returns. For any single security i, the model can be presented as

$$R_{it}=\alpha_i+\beta_i R_{mt}+\varepsilon_{it}\varepsilon_{it}, \text{with } E(\varepsilon_{it})=0, \operatorname{var}(\varepsilon_{it})=\sigma\varepsilon it2 \quad , \qquad (2)$$

where R_{it} = : return of a share i on the event day t; $\alpha_{it}=$: intercept term; $\beta_i=$: slope coefficient associated with the return of the market portfolio m; R_{mt}=: return of the market portfolio on event day t; $\varepsilon_{it}=$ the zero mean disturbance term [12][7].

The market model is considered to be a more advantageous approach compared to the constant mean return model. It excludes the changes in returns, which are caused by the fluctuations in the market, as a result, the variance of abnormal returns decreases as well. This means a more precise estimation of event effects [13][8].

[6] Although it seems to be basic in its form, S.J. Brown, J.B. Warner (1980, 1985) found that it often provides similar results with more advanced models.

[7] Following C.J. Corrado (2011), by assumption inherent in the structure of the market model, the firm-specific return ε_{it} shows no relation to the overall market and has an expected value of zero.

There are also other statistical models, which can be used as benchmark model for modeling normal returns. The most widely used are, for instance, multifactor statistical models. Some of them use industry indices additionally to market indices [14][9], other calculate the abnormal returns based on the difference in the expected performance of analyzed security and performance of a group of firms of similar size, which is usually expressed through market value of equity. This approach inherently assumes that expected returns coincide with market value of equity. Nevertheless, the benefits of using multifactor models in the event studies are limited. Empirical tests show that the explanatory power of additional factors that they strive to analyze is small and results only in an insignificant reduction of variance of abnormal returns, which is the major reason these models are applied for. The application of other models depends very often on the data availability. For example, in case of limited data the market-adjusted return model can be implemented. It is also applicable for the securities that are not traded in the stock markets for long time, so that their normal performance in pre-event period cannot be analyzed and they do not fit classical model. One example for the application of this model is the studies on initial public offerings [15].

Economic models add some restrictions on statistical ones and offer more strictly defined normal return models. Two most popular economic models are the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT). The CAPM was introduced by W.F. Sharpe (1964) [16] and J. Lintner (1965) [17] and can be defined as an equilibrium theory where the expected return of a security is determined by its covariance with the market portfolio [18][10]. The share return applying the CAPM is calculated as

$$\mathrm{R}_{it} = \mathrm{R}_{ft} + \beta_i\left(\mathrm{R}_{mt} - \mathrm{R}_{ft}\right) + \varepsilon_{it}, \text{with}\, \beta_i = \mathrm{cov}\left(\mathrm{R}_i, \mathrm{R}_m\right) / \sigma^2_{\mathrm{R}_m}\ , \qquad (3)$$

where

R_{ft} : risk-free rate;

$\mathrm{cov}(\mathrm{R}_i, \mathrm{R}_m)$: covariance between the returns of share *i* and the market portfolio *m*;

$\mathrm{cov}\left(\mathrm{R}_i, \mathrm{R}_m\right) / \sigma^2_{\mathrm{R}_m}$: variance of the returns of market portfolio *m*.

Nevertheless, also here the results of empirical studies outline some possible deviations from CAPM, which means that the power of restrictions imposed by CAPM on market models is limited. Taking into consideration the higher complexity of the model and its low marginal benefits, application of the CAPM is rather low [19][11].

[8] According to A.C. MacKinlay (1997), the advantages from using the market model depend on R2 in the market model regression. If R2 is large, the reduction of variance in abnormal return and potential benefits are also large.

[9] Sharpe (1970) and W.F. Sharpe, J.A. Gordon, J.V. Bailey (1995) offer in discussions of different index models with factors which are based on industry classification.

[10] An extensive explanation of the model, its advantages and shortcomings as well as its possible applications in practice is introduced by D.W. Mullins (1982).

[11] By extrapolating the values of the regression analysis in determining the cost of equity, the CAPM assumes constant conditions. Hence, it does not consider, for example, that the change of owners of the target company may significantly impact the risk situation of the company (G. Mandelker (1974)). In absence of coherent theories on how to modify i in case of an acquisition and in light of the criticism in the literature of the CAPM's restrictive assumptions, many scholars use the Arbitrage Pricing Theory ("APT") instead.

The second economic model is Arbitrage Pricing Theory (ATP). It was introduced by S.A. Ross (1976) [20] and can be defined as an asset pricing theory, which measures the expected returns of a particular asset as a linear combination of its multiple risk factors [21][12]. Some of these factors, which are the most important, behave similarly to the market. Other factors, which are additional ones, add only little explanatory power into the model. As a result, also here we can conclude that benefits of APT models compared to market models are small. The major purpose of ATP models is to reduce the biases of the CAPM models. As statistical models can also easily fulfill this goal, they continue to dominate in the event-study methodology.

Throughout the reviewed event studies, almost all of them used the statistical model, the CAPM model was only employed by A. Zaremba, M. Plotnicki [22] (2016). None of the studies applied APT. The vast majority of the studies applied the market model, two authors [23, 24] computed the expected share price based on the market- adjusted return model. For one study no information with regard to the applied model could be found [25].

In line with benchmark model, the choice of estimation window (control period for the modeling of normal returns) is important. Traditionally, this is a period ending a few days before the event date, so that the estimation window and the event window show no overlaps (see *Fig. 2*). This design helps to estimate the correct parameters for normal returns, which are not affected by the returns around the event[13].

The event is typically indicated by t=0, while the time index t counts "event time", i.e. the number of periods (days, months) from the event and not the usual calendar time. The estimation window is chosen in the period preceding the event. Typically, a value of n=250 days is used to correspond approximately to the number of trading days in a calendar year. The estimation period ends several days before the event day, so that estimation window and event window do not have any overlaps.

Within the observed studies, the estimation period varies from 59 days to 504 days, whereby most studies use an estimation period between 180 and 250 days [26, 27].

- **Step (iii): Calculation of the abnormal returns of a security around the event day**

The abnormal returns (AR) are "the actual ex post returns of the security over the event window minus the normal returns of the firm over the event window" [13, p. 15] and reflect the estimated effect of the event on share price. AR are calculated by subtracting the estimated return from the actual return, i.e. the change of closing price of the share on an event day compared to the previous day, typically while considering dividend payments [28][14]:

[12] Bhagat/Romano (2001), use ATP model in their study and compute expected returns as $R_{it} = \delta_0+\delta_{i1}F_{1t}+\delta_{i2}F_{2t}+\ldots+\delta_{in}F_{nt}+\varepsilon_{it}$, where $F_1, F_2, \ldots, F_n$ are the returns of the n factors that generate returns, and $\delta_{i1}, \delta_{i2}, \ldots, \delta_{in}$ are the factor loadings.

[13] The inclusion of event window into the model for estimation normal returns can increase the impact of event returns on the assessment of normal performance.

[14] In case of uncertainty whether the public announcement was made before or after the trade closing on the stock market, the returns from the following day are sometimes included.

$$\mathrm{AR}_{it} = \mathrm{R}_{it} - \mathrm{E}(\mathrm{R}_{it}), \tag{4}$$

where

AR_{it} : abnormal return of the share *i* on event day *t*;

R_{it} : actual return of the share *i* on event day *t*.

Assuming $\mathrm{E}(\varepsilon_{it})=0$ [15] and adjusting the observed event data return R_0 through subtracting the conditional expected return specified in equation (3), yields an abnormal return

$$\mathrm{AR}_{it} = \mathrm{R}_{it} - \mathrm{E}(\mathrm{R}_{it}) = \mathrm{R}_{it} - (\alpha_{it} + \beta_i \mathrm{R}_{mt}) \quad , \tag{5}$$

where

AR_{it} : abnormal return of the share i on event day *t*;

R_{it} : actual return of the share i on event day *t*;

α_i: intercept term;

β_i: slope coefficient associated with the return of the market portfolio *m*;

R_{mt} : return of the market portfolio on event day *t*.

This basic form of the market model can be adjusted by including an industry-specific market index or by computing logarithmic expected returns, though comparisons between the results of the market model and its logarithmic alteration have not shown statistically significant differences [3].

In the next step, the single values of abnormal return are aggregated in order to draw overall conclusion about the abnormal performance around the event. The addition can be done along two dimensions – through time and across securities. Assuming there are *N* firms in the sample, we can construct a matrix of abnormal returns of the following form:

$$\begin{pmatrix} \mathrm{AR}_{1,t_1} & \dots & \mathrm{AR}_{N,t_1} \\ \dots & & \dots \\ \mathrm{AR}_{1,-1} & \dots & \mathrm{AR}_{N,-1} \\ \mathrm{AR}_{1,0} & \dots & \mathrm{AR}_{N,0} \\ \mathrm{AR}_{1,1} & \dots & \mathrm{AR}_{N,1} \\ \dots & & \dots \\ \mathrm{AR}_{1,t_2} & \dots & \mathrm{AR}_{N,t_2} \end{pmatrix} \tag{6}$$

Each column of this matrix is a time series of abnormal returns for firm *i*, where the time index *t* is counted from the event date. Each row is a cross section of abnormal returns for time period *t*.

[15] ε_{it} =0 means that the mean disturbance equals zero.

The informativeness of the analysis can be improved by averaging the information over a number of firms[16]. Typically, we use the unweighted cross-sectional average of abnormal returns in period t for analysis:

$$\mathrm{AAR}_t = \frac{1}{N}\sum_{i=1}^{N} \mathrm{AR}_{it} \quad , \tag{7}$$

AAR_t : average abnormal returns of all shares in the sample on the event day t;

N : number of transactions in the sample.

To calculate the performance for the complete event window we have to add the abnormal returns (AR) from the first day of the event period, t_1 up to day t_2, achieving the cumulative abnormal returns for the security i in the event window t (CAR_i):

$$\mathrm{CAR}_i = \mathrm{AR}_{i,t_1} + \ldots + \mathrm{AR}_{i,t_2} = \sum_{i=t}^{N} \mathrm{AR}_{i,t_n} \quad . \tag{8}$$

In turn, the CAR*s* for a single security can be aggregated over the cross-section of events to obtain cumulative average abnormal returns (CAAR).

$$\mathrm{CAAR} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{CAR}_i \quad . \tag{9}$$

CAAR reflects the shareholder value created or destroyed through the acquisitions in the event window [29][17]. Large deviations of average abnormal returns from zero indicate abnormal performance. Arguing that percentage based returns do not sufficiently capture the actual change in shareholder wealth, some authors have also estimated dollar abnormal returns or value- weighted abnormal returns [30][18].

- **Step (iv): Designing a framework for testing the abnormal returns**

Having estimated the normal returns and measured the performance around the event, we calculated the abnormal returns. In the next step, we must design a framework to test the calculated returns. An important consideration at this stage is how to define the null-hypothesis and which methodology to use in order aggregate the abnormal returns for all firms included into the data sample.

The null hypothesis (H_0) states, conventionally, that the event has no effect on the behavior (which means statistically on mean or variance) of abnormal returns. Under the formulated H_0, the distributional properties of abnormal returns can be used to draw

[16] In order to study changes in share prices around events, the returns of each single firm can be analyzed separately. However, this is not always informative because the changes in stock price movements can be caused by information, which is not related to the event under study.

[17] It should be pointed out that the observed abnormal returns for each day within the event window are simply added rather than multiplied, as it is customary in the finance literature. For critique of this arithmetic method refer, for example, to G. Dissanaike (1994).

[18] For value-weighted returns the dollar abnormal returns across the samples are divided by the aggregate market capitalization of acquirers.

conclusions over any period within the event window. So, the distribution of abnormal returns for any single observation in given event window is

$$\mathrm{AR}_{it} \approx N\left(0, \sigma^2\left(\mathrm{AR}_{it}\right)\right) \quad . \tag{10}$$

For the cumulative abnormal returns under H_0, the distribution can be expressed as following:

$$\mathrm{CAR}_i\left(t_1, t_2\right) \approx N\left(0, \sigma_{\mathrm{i}}^2\left(t_1, t_2\right)\right) \quad [31]^{19}. \tag{11}$$

Under assumption of the null distribution for both abnormal returns and cumulative abnormal returns, we can complete the tests of null-hypothesis.

This result applies to a sample of one event and must be extended for the all securities in a sample. To perform aggregation for the entire event window and across all observations of the event, we assume zero correlation across abnormal returns of different securities, which means there is no clustering and no overlap in the event windows of the included securities [31][20]. Since under the null hypothesis the expectations of the abnormal returns are zero, the final conclusion about the cumulative abnormal returns can be drawn based on

$$\mathrm{CAR}_i\left(t_1, t_2\right) \approx N\left(0, \mathrm{var}\left(\mathrm{CAR}\left(t_1, t_2\right)\right)\right) \quad . \tag{12}$$

In practice, however, σ_i^2 is usually unknown. Therefore, we use an estimator to calculate the variance of the abnormal returns. It can be done as following:

$$\mathrm{var}\left(\mathrm{AR}_t\right) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_{\varepsilon i}^2 \quad . \tag{13}$$

For example, we can use the sample variance measure of $\sigma^2_{\varepsilon i}$ from the market model regression in the estimation window. Putting it into (12) to calculate var(AR_t), H_0 can be testing using

$$\Theta_1 = \frac{\mathrm{CAR}_{(t_1, t_2)}}{\mathrm{var}\left(\mathrm{CAR}_{(t_1, t_2)}\right)^{1/2}} \approx N(0,1) \quad . \tag{14}$$

[19] Under the same approach we can constrict a test of H_0 for security i using the standard cumulative returns, so that $\mathrm{SCAR}_{i(t1,t2)} = \mathrm{CAR}_{i(t1,t2)} / \sigma_{i(t1,t2)}$ Under the null hypothesis the distribution of $\mathrm{SCAR}_{i(t1,t2)}$ is student t with L_1-2 degrees of freedom. For a large estimation window (for example, L_1>30), the distribution of $\mathrm{SCAR}_{i(t1,t2)}$ will be well approximated by the standard normal. For detailed discussion see J.Y. Campbell, A.W. Lo, A.C. MacKinlay (1997).

[20] According to J.Y. Campbell, A.W. Lo, A.C. MacKinlay (1997), defined distributional assumptions and no overlap imply that (cumulative) abnormal returns are independent across securities. Also A.C. MacKinley (1997) assumes that event windows of N securities do not overlap and sets the covariance terms to zero, in order to calculate the variance estimator.

Some modifications to this basic approach are possible [31][21]. One possible example is the standardization of each abnormal return based on an estimator of its standard deviation. In some cases, such approach can even lead to more powerful results [32][22].

If we focus on a single null hypothesis – that the given event has no influence on the returns – either a mean effect or a variance effect will show a violation. In some cases however, we may be interested in testing only for the mean effect. To do so, it is necessary to expand the null hypothesis in the way that is accommodates the changing (usually increasing) variances. In this case, we usually eliminate the variance of aggregated cumulative abnormal returns by using the cross-section of cumulative abnormal returns to form an estimator of the variance, and then test the null hypothesis [33][23].

This "cross-sectional approach" for the estimation of variance is usually applied to average cumulative abnormal return [31][24] ($\text{CAR}(t_1,t_2)$). We can build an estimator of the variance using the cross-section as following:

$$\operatorname{var}\left(\overline{\text{CAR}}_{(t_1,t_2)}\right)=\frac{1}{N^2}\sum_{i=1}^{N}\left(\text{CAR}_{(t_1,t_2)}-\overline{\text{CAR}}_{(t_1,t_2)}\right)^2 \ . \qquad (15)$$

As the estimator of the variance must be consistent, an important condition here is that abnormal returns are not correlated in the cross-section. Usually, a sufficient assumption to satisfy this condition is an absence of clustering. Important is also that cross-sectional homoscedasticity is not required in this case. Provided the variance estimator is estimated correctly, the null hypothesis that the cumulative abnormal returns equal zero can then be tested applying classical approach.

- **Step (v): Analyzing the results and measuring its statistical significance**

As the final step, the statistical significance of the daily average and cumulative abnormal returns needs to be assessed. In other words, we test the probability of rejection of the null-hypothesis for given abnormal returns and given event-window and therefore evaluate the power of tests. Which statistical test of this hypothesis is appropriate depends on the way in which the abnormal returns are constructed and on the statistical properties of stock returns.

The ability to identify the presence of non-zero abnormal returns statistically is an important part of an event study. If it is impossible to distinguish between the null hypothesis and other alternatives, it would suggest that we need to change the design of

[21] Another method of aggregation is to assign equal weights to the single SCAR_i's. However, according to J.Y. Campbell, A.W. Lo, A.C. MacKinlay (1997), empirical studies show that choice of the approach has little effect on the results, because the variance of CAR is similar across securities.

[22] J.M. Patell (1976) introduces a test based on standardization, while S.J. Brown, J.B. Warner (1980, 1985) present a comparison between the standardization and basic approach.

[23] E. Boehmer, J. Musumeci, A.B. Poulsen (1991) introduce a methodology that accommodates changes in variance. It is best applied using the constant-mean-return model to measure abnormal returns.

[24] This approach can be also applied to the average standardized cumulative abnormal returns ($\text{SCAR}_{(t1,t2)}$).

the study. There are different possibilities to evaluate the power of tests [13][25]. The summary of widely used event-study tests is shown in the *Fig. 3*.

The best way to evaluate the statistical power is to use the given parameters and objectives of study. These tests are called parametric tests, because they rely on specific assumptions that are usually made about the distribution of abnormal returns in a given event-study. However, if the power seems to be insufficient, we must look for other opportunities to increase it. For instance, we can increase the size of the data sample, choose a shorter event window, or develop more strict restrictions for the test.

The key assumptions the parametric tests rely on are that the individual firm's abnormal returns are normally distributed and the residuals are not correlated across securities, so that the standard statistic is

$$t = \mathrm{AR}_0 / S(\mathrm{AR}_0)\ , \tag{16}$$

where $S(\mathrm{AR}_0)$: an estimate of standard deviation of the average abnormal returns $\sigma(\mathrm{AR}_0)$.

For the cross sectional independence across securities we can form estimator of variance as following:

$$\sigma^2(\mathrm{AR}_0) = \sum_{i=1}^{N} \frac{\mathrm{AR}_{i0}}{N} = \frac{1}{N^2} \sum_{i=1}^{N} \sigma^2(\mathrm{AR}_{i0})\ . \tag{17}$$

In the next step, we estimate the standard deviation of average abnormal returns for each security $\sigma(\mathrm{AR}_0)$, based on the standard deviation of the time series of abnormal returns of each firm in the estimation period (T weeks). The formula of statistics can be summarizes as following [34][26]:

$$\mathrm{S}(\mathrm{AR}_i) = \sqrt{\frac{\sum_{t=1}^{T} \left[\mathrm{AR}_{it} - \frac{\sum_t \mathrm{AR}_{it}}{T} \right]}{T - d}}\ . \tag{18}$$

For CAR, which were presented in (9), a standard test statistic[27] can be expressed then as CAR divided by an estimate of its standard deviation [4, 5][28], so that it is given by

[25] A.C. MacKinley (1997) suggest evaluating the power of the tests or the question of the probability of rejecting the null hypothesis for a specified level of abnormal return, using analytical approach. They construct eight alternative hypothesis using four levels of abnormal returns (0.5%, 1.0%, 1.5%, and 2.0%) and two levels for the average variance of the cumulative abnormal return of a given security over the sampling interval, 0.0004 and 0.0016. However, if these distributional assumptions are imprecise, then the power calculations may be inaccurate. Nevertheless, J.S. Brown, J.B. Warner (1985) explored this issue and found that analytical calculations and empirical power are very similar.

[26] Following A.P. Serra (2002), we assume the student-t distribution with *T-d* degrees of freedom to test this statistic under the null hypothesis.

[27] For any given performance measure (e.g. CAR), a test statistic is usually calculated and related to its assumed distribution under the null hypothesis. if the test statistic exceeds a critical value, which usually equals 5% or 1% tail region (i.e., the test level or size of the test is 0.05 or 0.01), the null-hypothesis will be rejected.

[28] An alternative method is a test statistic that adds standardized abnormal returns. This implies that each observation is weighted in inverse proportion of standard deviation of the estimated abnormal returns. The standard

$$t = \frac{\mathrm{CAR}_{(t_1, t_2)}}{\sigma^2(t_1, t_2)}, \text{ with } \sigma^2_{(t_1, t_2)} = L\,\sigma^2(\mathrm{AR}_t) \quad , \tag{19}$$

where $\sigma^2(\mathrm{AR}_t)$: the variance of the one-period mean abnormal return.

The formula assumes that time-series are independent from one-period mean abnormal returns and shows that CAR have a higher variance in case of larger L. It is usually expected that test statistic is unit normal under the null-hypothesis, which however remains only an approximation, because of application of the standard deviation.

Under condition that the variance of one-period mean abnormal returns is estimated precisely, the standard deviation shown in equation (18) is clearly defined. However, the assumption about independence of cross-sectional abnormal returns is often broken by the event-time clustering[29]. To address this bias, the significance of average abnormal returns in a specific event-period is often measured based on the variability of the time series of event portfolio returns in the period before or after the event day. For example, J.S. Brown, J.B. Warner [4, 5] (1980) suggest that standard deviation of average residuals must be calculated using the time series of average abnormal returns in the estimation period.

The major goal of standardization is to make sure that the variance of every single abnormal return is the same [31][30]. If we divide each single firm's abnormal residual by its standard deviation, which is calculated over the estimation period, we can estimate that the variance of each residual is 1. The standardized residuals can be presented as:

$$AR_{i0} = AR_{i0} \,/\, S(\mathrm{AR}_i) \quad . \tag{20}$$

The test statistics for the hypothesis that average standardized residuals across firms in a given event week are equal to zero is calculated as following:

$$z = \frac{\overline{\mathrm{AR}_0}}{\mathrm{S}(AR_0)} = \frac{\frac{1}{N}\sum_{i=1}^{N} \mathrm{AR}_{i0}}{\mathrm{S}(\overline{\mathrm{AR}_0})} \quad . \tag{21}$$

Another standardized statistic to test the null hypothesis (the acquisition has no impact on shareholder value) is introduced by P. Dodd, J. Warner [9] (1983). Within this test statistic average standardized abnormal returns (SAR_t) are calculated as follows:

deviation of abnormal returns is calculated using time-series return data for each single firm. J.S. Brown, J.B. Warner (1980, 1985) claim that the application of standardized abnormal returns can be superior under certain conditions, however, in short-term event studies it makes little difference.

[29] This would lead to biases in the standard deviation estimate downward and the test statistic given in equation (5) upward.

[30] For example, following J.Y. Campbell, A.W. Lo, A.C. MacKinlay (1997), you can build a sample of event firms and calculate time-series of daily abnormal returns for the entire sample for a number of days (e.g. 180 days) before the event. The standard deviation of the sample returns can be applied to measure the significance of average abnormal returns in your event-window. We also need to evaluate the cross-sectional dependence, because the variability of sample returns usually incorporates all possible cross-dependences among single securities and returns in time.

$$\overline{\mathrm{SAR}}_t = \frac{1}{N}\sum_{i=1}^{n}\frac{\mathrm{AR}_{it}}{S}, \text{ with } \hat{s}_{it} = s_i\sqrt{1+\frac{1}{L}+\frac{\left(\mathrm{R}_{mt}-\overline{\mathrm{R}_m}\right)^2}{\sum_{\tau=\tau_1}^{\tau_2}\left(\mathrm{R}_{m\tau}-\overline{\mathrm{R}_m}\right)^2}}\ , \tag{22}$$

where $\overline{\mathrm{SAR}}_t$: average standardized abnormal return on event day t;

s_i : standard deviation of share i's abnormal returns during the estimation period;

L : number of days of the estimation period;

R_{mt} : return of the market index for event day t;

$\overline{\mathrm{R}_m}$: average return over the market index during the estimation period;

$\mathrm{R}_{m\tau}$: return on the market index on day τ of the estimation period.

The test statistics for average abnormal returns on a single day t and cumulative abnormal returns for the event window T are calculated as shown in equations [9][31]:

$$Z_{\mathrm{AR}_t} = \left(\sqrt{n}\right)\overline{\mathrm{SAR}}_t\ , \tag{23}$$

$$Z_{\mathrm{CAR}_T} = \sqrt{\frac{n}{\left(t_2-t_1+1\right)}}\sum_{t=t_1}^{t_2}\overline{\mathrm{SAR}}_t\ , \tag{24}$$

where

Z_{AR_t} : test statistic for average abnormal return for event day t;

Z_{CAR_T} : test statistic for cumulative abnormal return for event window T;

$t_2 - t_1 + 1$: number of days in the event window T.

Assuming that the abnormal returns are normally distributed, the shares' residuals are not cross-sectional correlated, and the event-induced variance is insignificant, these test statistics follow the standard normal distribution $N(0,1)$.

While the power and specification of statistical tests can be clearly determined, the economic interpretation of results is less straightforward. As almost all tests are joint tests, which means that they are well-defined as long as the underlying assumptions are correct, the choice of analytical model and identification of statistical properties can influence results significantly. A good example is a standard t-test for average abnormal returns. As discussed earlier, one of the assumptions of the test is that the average abnormal returns for cross-section of securities are normally distributed. According to possible specifications of the test, some additional assumptions can be made about the independence in time-series or cross-section. The effectiveness of such assumptions remains often an empirical question [10, 17][32].

[31] P. Dodd, J. Warner (1983) point out that if most CARs are positive and the sample includes a few extreme genitive outliers with large standard deviations, the CARs and test statistic may have opposite signs.

Another important problem is outlined by E. Boehmer, J. Musumeci, A.B. Poulsen (1991) [33]. He claims that the variance of stock returns increases on the event date and as a result of this, tests that measure the variance of average abnormal returns using the time series in the period preceding the event (e.g. estimation period) reject the null-hypothesis too often. He suggests that the variance of average abnormal returns should be estimated based on cross-section of event date prediction errors. In case of standardized residuals, this proposition can be expressed as following:

$$S\left(\mathrm{AR}_0\right)=\sqrt{\frac{1}{N(N-d)}\sum_{i=1}^{N}\left[\mathrm{AR}_{i0}-\frac{\sum_{i=1}^{N}\mathrm{AR}_{i0}}{N}\right]}\quad. \tag{25}$$

The methodology is based on assumption that the variance on the event date is proportional to the variance in the estimated period and is equal across securities. However, it is intuitively understandable that the larger the change in variance is, the less powerful is the test. In case of lower tailed alternative hypotheses, this parametric test rejects too often. One possible solution to increase the power of the test and interpretation power of results is to apply non-parametric tests.

Alternative non-parametric approaches include usually no assumption about the possible distribution of returns. The most common non-parametric tests used in event study methodology are the sign test and the rank test.

The sign test, which is calculated based on the sign of abnormal returns, assumes that (cumulative) abnormal returns are independent across securities and propose that the share of positive abnormal returns under the null hypothesis is 0.5. The underlying idea of the test is that in case of null hypothesis it is equally probable that CAR are either positive or negative. For example, if we expect positive abnormal returns associated with a given event, the null hypothesis is H_0:p<=0.5 and the alternative is H_A:p>0.5, where p=pr(CAR>=0.0). In order to calculate the test statistic, we need to know the number of events when the abnormal returns are positive N+, and the total number of events N.

One disadvantage of the sign test is that it may be not clearly-defined in case the distribution of abnormal returns is skewed, which often happens with daily data. To address this weakness, C. Corrado (1989) [14] introduced a non-parametric rank test for assessment of abnormal performance in event studies [37][33].

To apply the rank test, we first need to assign each firm's abnormal returns a rank (Ki) over the combined period that includes both estimation and event window (Ti) period:

$$K_{it}=\mathrm{rank}\left(\mathrm{AR}_{it}\right)$$

$$\mathrm{AR}_{it}>\mathrm{AR}_{is}=K_{it}>K_{is}\quad. \tag{26}$$

[32] This statement is especially significant for small samples, where we can not apply the central limit theorem (S.P. Kothari, J.B. Warner (2006)).

[33] A. Cowan, A.M.A. Sergeant (1996) prove that C. Corrado's rank test offer better statistical power than parametric tests if the returns' variance does not increase. In case this happens, it can lead to wrong results.

In the next step, we compare the ranks assigned for each firm in the event window with the expected average rank under the null hypothesis, where Ki =0.5 +Ti/2. After that, we apply following test statistic for null hypothesis:

$$\mathrm{R} = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(K_{i0}-\overline{K}_i\right)}{S\left(\overline{K}\right)}, \text{where } S\left(\overline{K}\right)=\sqrt{\frac{1}{N}\sum_{i=1}^{T}\frac{1}{N^2}\sum_{i=1}^{N}\left(K_{it}-\overline{K}_1\right)^2} \quad . \tag{27}$$

For the given statistic we assume that it is distributed comparable to unit normal. In case of multi-week event periods, the rank statistic can be calculated as following:

$$\mathrm{R} = \frac{\sum_{i=1}^{L}\frac{1}{N}\sum_{i=1}^{N}\left(K_{il}-\overline{K}_i\right)}{\sqrt{\sum_{i=l}^{L}S^2\left(\overline{K}\right)}} = \frac{\sum_{i=l}^{L}\overline{K}_l}{S\left(\overline{K}\right)}\frac{1}{\sqrt{L}} \quad . \tag{28}$$

Also here, provided that there is no cross-sectional correlation, we assume the normal distribution of the statistic.

Typically, all non-parametric tests offer not a substitution but an extension to parametric one and are usually applied additionally to parametric tests. Complimentary application of non-parametric tests helps to check the robustness of conclusions made based on parametric tests [38][34]. This is also reflected in the overview of recent event-studies. The majority of authors used the parametric tests to analyze the significance of results. Three studies present the results of both parametric and non-parametric tests [39, 40, 41]. Only one author relies on solely one non-parametric sign test [42].

2. Overview of the Recent Event Studies

The number of conducted event studies over the last decades is quite large and include different industries, cross-border and domestic acquisitions, while using different observation periods and size of the transaction sample. *Fig. 4* gives an overview of the 15 event studies, which were fulfilled from 2015 till 2020 and should give more detailed overview of recent research.

While the reviewed studies include transaction from different industries including either all or only non-financial, non-utility business sectors, five studies solely measure cumulative abnormal returns for acquisitions in a single industry, e.g. banking [25, 27, 43], logistic services [39] and high-tech [40]. Six studies focus on the developed markets, nine studies are concerned with transactions in emerging markets, incl. BRICS, EMEA, CEE, and ten studies analyze the cross-boarder deals. Two studies focus solely on Asian markets and report cumulative abnormal returns for the acquirers in the Indian domestic market [32, 41]. One study analyses the transactions in the Chinese and Hong Kong capital market [44].

[34] C.J. Campbell, C.E. Wasley (1993) outline the benefits of such check. They show empirically that non-parametric ran test offer more powerful results for analysis of daily stocks traded on NASDAQ, compared to standard parametric tests.

For the review only those studies were analyzed which were performed in the time period from 2015 till 2020. However, overall they include different time periods in their analysis. So, eight studies also included transactions during the 1990s in their sample, and not all of them split their findings by the different time periods. Nevertheless, the majority reflects the period from 2000 till 2015. The size of the analyzed samples ranges from fourteen transactions to over eight thousand transactions [27, 42, 43]. The average sample size is therefore 473.

Besides the analysis of cumulative abnormal returns and wealth creation for shareholders, most studies also aimed to identify its underlying determinants using different factors of the transaction, such as method of payment, strategic rationale, hostility of the bid, number of bidders, market power of the target, geographic presence. The significance of the impact of those determinants was measured in univariate and/or cross-sectional analysis. Four studies apply multiple regression analysis to verify the results [24, 39, 45, 46].

3. Evaluation and Methodology

Event studies is the most successful application in the area of corporate finance and currently the most accepted methodology for measuring the implications of M&A from the perspective of shareholders of the involved entities. Their dominance can be attributed to various attractive features (see *Fig. 5*):

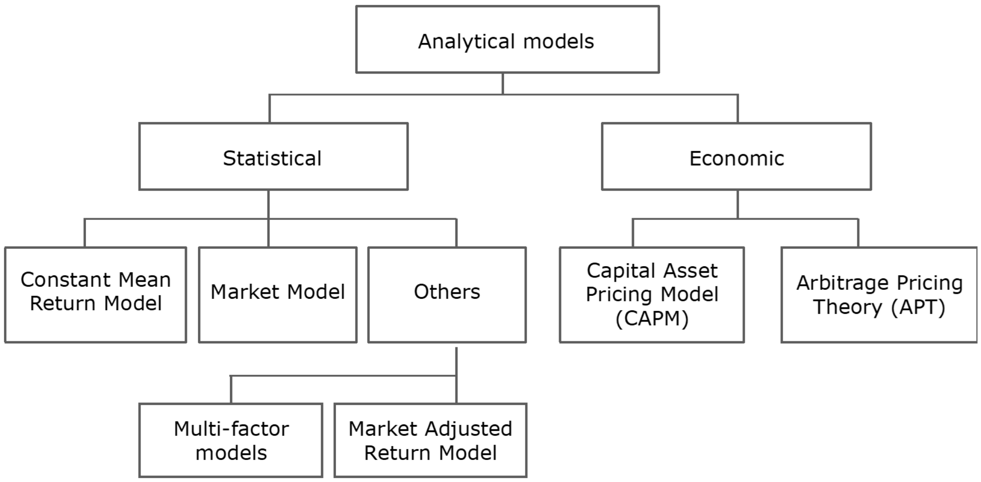
A major success of event study methodology is related to the fact that the U.S. Supreme Court accepts the results of event-studies in different cases, e.g. determining materiality in insider trading and determining discharge amounts in the case of fraud [6][35]. Another point that is worth mentioning is that methodology is quite simple and market data, which is used for the analysis, is available through the main financial databases. This makes the empirical research with large sample of securities possible. Furthermore, share prices incorporate direct expectations of investors and reflect better the value created by an event compared to data from financial statement analysis, which often have contamination problems. The information included in share prices can also be considered future-oriented and be used for forecasts.

At the same time, methodology has some limitations. In cases, where the date of event is can not be identified, event-study is less useful[36]. It also basically assumes efficiency of capital markets and the fact that there is no information available before the public announcement of M&A, which in practice often not the case. It also implies a linear relationship between the systematic risk and share return, which is questionable.

[35] M.L. Mitchell, J.M. Netter (1994) discuss the importance of event studies for securities law.

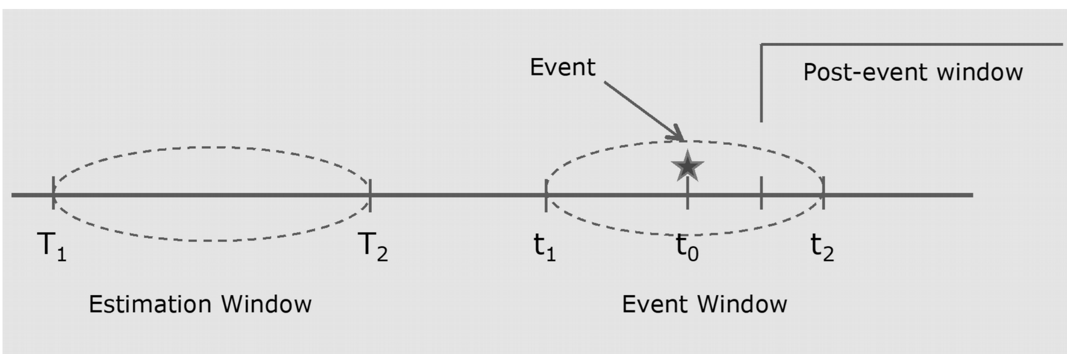
[36] For instance, it is difficult to measure the impact of regulatory changes on particular stocks, using event-study methodology.

Figure 1
Models of measuring expected performance



Source: Authoring based on [13]

Figure 2
Calculation of estimation window



Source: Authoring

Figure 3
Analytical tests applied to test the Null-Hypothesis

	Parametric	Non-parametric
Key assumptions	Individual firm's abnormal returns are normally distributed & residuals are not correlated among industries	Free of specific assumptions concerning the distribution of returns
Key concept	Estimation of standard deviation on the basis of the standard deviation of the time series of abnormal returns of each firm	Analysing of the firms abnormal returns according to sign of abnormal return (Wilcoxon, 1945), or given rank (Corrado, 1989)
Modifications	Brown/Warner (1980) Boehmer (1991) Dodd/Warner (1983)	Usually used only in conjunction with parametric tests

Source: Authoring

Figure 4
Overview of recent event-studies

	Year	Sample period	Sample size	Industry coverage	Acquirer Nation	Target Nation	Analytical model	Estimation period	Event window (days)	Tests/Multiple Regression	Outcomes
Tao et al.	2020	2000-2012	165	All	China	All, outside China	MM	n.a.	(-1;1), (-2;2), (-5;5)	parametric/ no	acquirers earn positive AR of 1.22%, different results in China & HongKong market
Pandey/Kumari	2020	2010-2020	14	Banking	India/US	India/US	MM	(-90;-31)	(-30;+30), (30;50)	parametric/ no	acquirers earn negative AR, Indian market is more sensitive than US
Firk et al.	2019	2005-2011	2787	All, exl. Fin	Europe (16), US	World	MM	(-200;-11)	(-3;+3), multiple	n.a./ yes	no confirmation that Value Based Management leads to superior M&A returns
Mall/Gupta	2019	2000-2018	383	Banking	India	India	n.a.	n.a.	(-10;+10)	n.a./ no	consolidation in banking sector leads to positive AAR and wealth creation for bidders
Chuang	2018	2000-2013	8029	All, exl. Fin, Utiity	US	All	MM	(-270;-61)	(-1;1), (-2;2), (-5;5)	non-para-metric/ no	"glamour" acquriers earn lower returns than "value" acquirers
Adrian	2018	2015-2016	100	All	UK	All	MM	(-100;-10)	(-5;5), multiple	parametric/ no	domestic acquirers earn positive returns that turn to negatibe in long-run, international insignificant positive
Dell'Acqua et al.	2018	1997-2012	271	All	BRICS	Developed markets	MM, MAM	(-120;-20)	(-2;2)	parametric/ no	acquriers earn positive CAR of 0.28-0.45%
Ranju/ Mallikarjunappa	2018	2000-2016	90	HighTech	India, Inbound	India, Outbound	MM	(-282;-31)	(-30;+30)	parametric/ non-paramet-ric/ no	wealth creation for both bidders and targets with 1.52% and 3.12%, respectively
Kiesel et al.	2017	1996-2015	826	Logistics Services	All	All	MM	(-262;-11)	(-5;5), multiple	parametric/ non-paramet-ric/ yes	acquirers earn positive AR in (-1;1) and (-5;5) with 1.31% and 1%, respectively
Arslan/Simsir	2016	2005-2011	105	All	All	Turkey	MM	(-819;-315)	(-1;1), multiple	parametric/ no	target earn returns that are almost twice as large as returns of acuqirers
Zaremba/Plotnicki	2016	2001-2014	109	All	CEE	CEE	MM, benchmark, zero-model	(-140;-21)	multiple	parametric/ no	acquriers earm almost >2% in short-run, value creation for both acquirers and targets
Karamanos et al.	2015	1996-2013	14	Banking	Greece	Greece	MM	n.a.	(-10;1)	parametric/ no	acqruiers earn insignificant positive returns, targets earn +7.44%, combined returns are 2.91%
Gregory/O'Donohoe	2015	1990-2005	288	All	All	UK	MAM	n.a.	(-2;2)	parametric/ yes	acquirers earn negative AR of -1.07%
Arik/Kutan	2015	1997-2013	1648	All	All	EMEA (20)	MM	(-250;-31)	(-1;1), multiple	parametric/ yes	target firms earn positive returns of +5.17%
Rani et al.	2015	2003-2008	522	All	India	All	MM	(-280;-26)	(-20;20), multiple	parametric/ non-paramet-ric/ no	acquriers earn positive returns during 2,3 and 5 days around announcement, long-tern returns are negative

Source: Authoring

Figure 5
Strengths and limitations of the event-study methodology

Strengths	Limitations
• Short-term event window allows to calculate precise market reaction on merger	• Choice of the event date is particularly important
• Market data used for calculation of CAR provides a direct measure of value created	• Model assumes the (semi-)effciency of capital market
• Share prices avoid data contamination problems inherent in financial statements	• It assumes the linear relationship between the systematic risk and share return
• Assuming that share prices incorporate information about future cash flows - the method is future oriented	• It relies on assumption that the capital market don't have information on merger prior to the initial public announcement
• Market data on securities is publicly available what makes reasearch and empirical studies easier	• Model does not take into account the confounding events during the period of analysis

Source: Authoring

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Conflict-of-interest notification

I, the author of this article, bindingly and explicitly declare of the partial and total lack of actual or potential conflict of interest with any other third party whatsoever, which may arise as a result of the publication of this article. This statement relates to the study, data collection and interpretation, writing and preparation of the article, and the decision to submit the manuscript for publication.