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Event studies with daily stock returns in Stata: Which command to use?

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Abstract. This article provides an overview of existing community-contributed commands for executing event studies. I assess which command(s) could have been used to conduct event studies that have appeared in the past ten years in three leading accounting, finance and management journals. The older command `eventstudy` provides a comfortable graphical user interface and good functionality for event studies that do not require hypotheses testing. The command `estudy` described in Pacicco et al. (2018, *Stata Journal* 18(2), pp. 416–476; 2020, *Stata Journal*, forthcoming) provides a set of commonly applied test statistics, useful exporting routines to spreadsheet software and LaTeX for event studies with a limited number of events. The most complete command in terms of available test statistics and benchmark models as well as its ability to handle events with insufficient data, thin trading and large samples is `eventstudy2`.

Keywords: event studies, estudy, eventstudy, eventstudy2

1 Introduction

Event studies represent a standardized method to measure and statistically assess stock price reactions to unanticipated events. For instance, Ball and Brown (1968) use this method to show that earnings surprises move stock prices. Fama et al. (1969) show that stock splits have a positive average impact on stock prices. Since the publication of these two seminal papers, event studies have become a workhorse method whenever researchers want to test whether any news event has an impact on stock prices. The scenarios range from dividend announcements (e.g., Asquith and Mullins 1983; Kane et al. 1984), mergers and acquisitions (e.g., Capron and Pistre 2002; Halpern 1983), changes in legislation and corporate litigation (for an overview, see Bhagat and Romano 2002a,b) to celebrity endorsement of products (e.g., Agrawal and Kamakura 1995), nuclear catastrophes (e.g., Bowen et al. 1983; Hill and Schneeweis 1983) and hurricanes (e.g., Lamb 1998).

In the past decades, several software solutions for conducting event studies have emerged, most notably the SAS-based EVENTUS® software, which has been directly embedded into the Wharton Research Data Services (WRDS) platform and thus has become a gold standard for event studies that are focused on US firms. Nevertheless, probably because only top-ranked universities and other top research institutions have access to WRDS and/or EVENTUS®, free event study software packages in other pro-

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gramming environments (e.g., R and Python) have become available. Also, Stata users can currently draw on three different community-contributed commands (in chronological order of their first appearance on the Statistical Software Components (SSC) server of the Boston College Department of Economics):

- `eventstudy` (Zhang et al. 2013)
- `eventstudy2` (Kaspereit 2015, updated November 2019)
- `estudy` (Pacicco et al. 2018, 2019, 2020)

In this article, I analyze which of the three commands is suitable for which type of event study. My analysis reveals that the chronological order of appearance does not represent stages of evolution. Instead, each command is applicable to different types and tasks within the universe of event study designs or has certain features which make it more or less suitable for specific types and tasks. The older command `eventstudy` provides a comfortable graphical user interface and good functionality for event studies that do not require hypotheses testing. The command `estudy` provides a set of commonly applied test statistics, useful exporting routines to spreadsheet software and LaTeX. The most complete command in terms of available test statistics and benchmark models as well as its ability to handle events with insufficient data, thin trading and large samples is `eventstudy2`.

My analysis is based on three pillars. First, I identify the conceptual characteristics of event studies. Instead of reiterating the statistical fundamentals of the event study method, which have already been presented elsewhere (e.g., Corrado 2011; Kothari and Warner 2007; MacKinlay 1997), I focus on what conceptually constitutes an event study, i.e., what researchers are aiming for when using this research design, and whether or how the three community-contributed commands meet these user demands. Second, I back my assertions by analyzing all event studies that have been published in three leading field journals, the Journal of Accounting Research, the Journal of Finance, and Management Science during the period 2009–2018. Third, I assess the practical features and limitations of the three commands with respect to run time, consistency and handling of thinly traded stocks.

My analysis does not focus on input and output routines since their usefulness is in the eye of the beholder while test statistics, benchmark models, maximum sample sizes and run times are established features. It should be noted, though, that in my opinion the oldest command `eventstudy` scores highest in the domain of data input because it is the only command that provides a graphical user interface (GUI). In the domain of input data, `eventstudy2` is the most complex command as it requires multiple .dta files (one for the event list, one for the security returns and one for the market or factor returns). On the one hand, it will potentially take longer for the user to fully understand it. On the other hand, this data input scheme is consistent with the data delivery formats of popular financial data providers such as CRSP, I/B/E/S and Compustat. The `estudy` command has the most comfortable output routines, including export to spreadsheet software and LaTeX.

2 Conceptual characteristics of event studies and community-contributed commands

2.1 Elements of event studies

In this section, I outline my framework of the three core elements, three supplemental elements, and two overarching principles of event studies, which will allow me to evaluate which of the three community-contributed event study commands are most suitable for which empirical setting. In this framework (see Table 1), the *event* leads the ranking of core elements because researchers are typically interested in measuring the impact of a specific event type on stock prices, e.g., earnings announcements, stock splits or dividend cuts. The *firm* and the event date (*time*) have to be properly identified but pose a methodological challenge rather than being at the center of the research. Since

Table 1: Elements and principles of event studies

Core elements	Supplemental elements	Overarching principles
1. Event(s)	· Macro-economic confounding event(s)	· Aggregation
2. Firms(s)	· Firm-specific confounding event(s)	· Synchronization
3. Time	· Statistical hypotheses testing	

firms per se are not important and the focus is on the event, stock price reactions are aggregated across firms to eliminate random variation in returns not associated with the event. This corresponds to the overarching principle of *aggregation* (Corrado 2011, p. 212). Nevertheless, the *firm* ranks second in my list of core elements because many event studies aim at identifying how the impact of an event depends on firm characteristics, e.g., firm size, magnitude of earnings surprise (Collins and Kothari 1989) or audit quality (Theo and Wong 1993). In fact, as my analysis in the next section will show, these cross-sectional type of studies constitute a majority (97 out of 180 sample articles). Firms as individual objects, however, are rarely the object of research interest and stock price reactions are either measured on an aggregated basis or are hypothesized to be in a functional (linear) relationship with firm characteristics.

Time ranks third because researchers are typically not interested in whether an event has an impact on stock prices on a particular calendar day. For instance, it is unlikely that a researcher wants to analyze whether a stock split affects stock prices differently when announced on March 3rd compared to September 15th. In fact, the event study method invokes the concept of event-time, which is a timeline relative to the event day. For instance, if a similar event took place for Firm A on March 3rd and Firm B on September 15th, calendar days March 2nd, 3rd, and September 14th, 15th and 16th, are redefined as days [-1], [0], and [+1], respectively. Thus, the researcher's or their software's first and very important task is to re-arrange the stock return data and put it onto a common timeline that is relative to the event dates. This corresponds to the

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overarching principle of *synchronization*.

The event study method distinguishes itself from a simple examination of stock returns by properly addressing the problem of *confounding events* and by defining test statistics (*statistical hypotheses testing*) that address various econometric issues. Confounding events are events other than the event of research interest that potentially impact stock prices. They can be of *macro-economic* (affecting all firms to some extent) or *firm-specific* (presumably only affecting one firm) character. The event study method is well-designed to eliminate the impact of macro-economic events without significant loss of observations. By calculating and assessing abnormal return relative to a market index or multiple factor model, the effect of overall market movements on event firms' stock returns can be effectively addressed (MacKinlay 1997, pp. 17–20). For instance, researchers can effectively address the effects of unanticipated changes in interest rates or terrorist attacks without even identifying these events. However, the event study method is incapable of addressing firm-specific confounding events. Those have to be identified by the researcher and taken into account by modifying the sample selection, potentially leading to some loss of observations.

2.2 Software requirements

From the above described elements of event studies, several desirable features of event study software solutions can be derived. They should assist the user in transforming the event and stock return data from common databases such as WRDS/CRSP (Center for Research in Security Prices), Datastream or Yahoo!Finance from calendar-time to event-time. To that end, the command should, based on a common stock identifier and a date variable, merge a list of events with a data set of stock returns. It should then re-arrange the data to achieve an event-time structure with the date variable taking a value of zero at the event date (synchronization). This data management task is very important because it can be very time-consuming and prone to error if executed manually using a spreadsheet software.

The second core task any complete event study software should be able to perform is the calculation of abnormal returns against a benchmark model. Standard benchmark models are the constant mean return model, the market model with a single market index as benchmark, and factor models such as the Fama and French (1993) three-factor model. Further, the software should be capable of calculating cumulative average abnormal returns and buy-and-hold average abnormal returns (Barber and Lyon 1997).

The third feature an event study software should have is the implementation of statistical testing to assess (cumulative) average abnormal returns against the null hypothesis of them being zero. In fact, most of the methodological literature on event studies centers around the specification and empirical power of different parametric and non-parametric test statistics such as the crude dependence adjustment t-test by Brown and Warner (1980, 1985), the Patell (1976) Z-statistic, the Corrado (1989) rank test, the Boehmer et al. (1991) parametric test with correction for event-induced volatility changes, the Kolari and Pynnonen (2010) adjustment of the Boehmer et al. (1991) test

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for cross-correlation, and the GRANK test for cumulative average abnormal returns (Kolari and Pynnonen 2011).

The fourth desirable feature of an event study software package is its ability to present results and other output. Test statistics and statistical significance level should be tabulated alongside (cumulative) average abnormal returns ((C)AARs). Further, a graphical presentation of cumulative average abnormal returns is desirable since this is a standard presentation format in journal articles. The event study software should report on events that had to be excluded and the reasons for their exclusion. Cumulative abnormal returns (CARs) should be made available for cross-sectional analysis.

2.3 Features of community-contributed commands

Table 2 summarizes the features of the three community-contributed commands. Although `eventstudy` and `eventstudy2` do not share any programming code, the latter can be considered a substantial extension of the former. While `eventstudy` and `eventstudy2` share the capability to synchronize data onto a common timeline that is relative to the events, `eventstudy` is restricted to the single factor model to calculate abnormal returns. `eventstudy` does not provide any hypothesis testing capabilities while `eventstudy2` provides plenty. However, `eventstudy` provides a GUI, which the other two commands are lacking. Thus, `eventstudy` can be used if researchers are exclusively interested in calculating CARs and are not interested in assessing statistical significance, or plan to assess statistical significance using their own routines. Although most of the methodological literature on event studies focuses on statistical hypotheses testing, the analysis of journal publications in the next section reveals that some studies do not apply these tests but are only interested in factors that explain abnormal returns. Therefore, the command `eventstudy` maintains its *raison d'etre* by being useful to researchers who can preserve run time by applying this less complex command.

Table 2 also presents the differences in features of `eventstudy2` and `estudy`. Since Pacicco et al. (2018, p. 461) state that their `estudy` command "significantly improves the existing commands in terms of both completeness and user comprehension", with reference to `eventstudy2`, these differences are highlighted by bold fonts. As `estudy`'s data input is organized in wide rather than long format, it allows approximately as many factors to be included in the benchmark model as the respective Stata version can take variables. It is well known in the literature that one factor, the market index, or at most up to five factors (Fama and French 2015) add some explanatory power to the benchmark model. In fact, it is commonly known that the incremental effect on explanatory power is minor for all factors beyond the market index (MacKinlay 1997, p. 18). On the other hand, the wide input data format of `estudy` imposes a restriction on the number of events. Pacicco et al. (2020, pp. 3–4) state that their command can execute event studies with more than 24 000 companies. According to the outcomes of my tests of the `estudy` command, this limit applies not only to the number of companies but also to the number of events. It is important to understand that 24 000 companies would not impose a strong limitation since, even in big markets such as the U.S., samples rarely consist of more than 24 000 distinct companies. However, there are many studies that

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Table 2: Features of community-contributed event study commands.

Feature↓ || Command→	eventstudy	eventstudy2	estudy
Data management (Synchronization)	YES	YES	YES **- Is able to use prices instead of returns**
Calculation of abnormal returns (Benchmark model)	- Market model	- Market model - Raw returns - Constant mean returns - Market adjusted returns - Factor model **(up to 12 factors)** **- Factor model with (G)ARCH** **- Buy-and-hold raw returns** **- Buy-and-hold abnormal returns**	- Market model - Raw returns - Constant mean returns - Market adjusted returns - Factor model **(up to maxvar)**
Hypothesis testing (Test statistics)		- t-test (assuming independence) **- t-test** **(crude adjustment)** - Patell Z-statistic - Adjusted Patell statistic - Boehmer et al. test - Kolari and Pynnonen test **- Generalized sign test** - Wilcoxon signed-ranks test **- Corrado rank test** **- Corrado and Zivney rank test** - GRANK test **- Bootstrapped t-ratio**	- t-test (assuming independence) - Patell Z-statistic - Adjusted Patell statistic - Boehmer et al. test - Kolari and Pynnonen test - Wilcoxon signed-ranks test - GRANK test
Presentation (Tabulating abnormal returns; reporting on dropped observations)	- (Cumulative) abnormal returns are available for cross-sectional testing	- Tabulation of average abnormal returns and significance levels - Tabulation of cumulative **average** abnormal returns and significance levels **- Comprehensive reporting on dropped events** - Graphical display of cumulative average abormal returns - (Cumulative) abnormal returns are available for cross-sectional testing	- Tabulation of cumulative **(average)** abnormal returns and significance levels - Graphical display of cumulative average abormal returns - (Cumulative) abnormal returns are available for cross-sectional testing **LaTeXformatted output tables** **Excel output of results**

operate with samples of fewer companies but considerably more events (e.g., Bhojraj et al. 2009; Hail et al. 2014; Savor and Wilson 2016).

The `estudy` command provides output and statistical hypothesis testing by event firms, which `eventstudy2` does not. However, researchers very rarely report abnormal returns and their statistical significance for each event firm separately because this would stand against the main idea of event studies of measuring the general effect of a specific type of event on firms, which corresponds to the above derived principle of aggregation (see Table 1). The event ranks first, the firm only second. In fact, the very fundamental idea of event studies is to measure the average impact of an event type on stock returns. This calls for aggregation of abnormal returns and allows the application of the law of large numbers to arrive at lower standard errors in hypothesis testing (Corrado 2011; MacKinlay 1997).

`eventstudy2` has the ability to calculate buy-and-hold abnormal returns and the respective bootstrapped t-ratio test statistic. It allows for different benchmarks for different event firms, which make the calculation of abnormal returns against characteristic-based benchmarks (Daniel et al. 1997), a method commonly used in finance and accounting research (e.g., Da et al. 2011), possible. It also reports on dropped observations or how it treats missing return observations while the other two commands are lacking these features.

To conclude on my conceptual comparison of the three community-contributed commands, I clearly see the relative merits of the `eventstudy` command if a researcher is interested in only calculating abnormal returns against the market model. `eventstudy` has a simple structure, which includes the most important data management tasks, and has a GUI that is most useful for unexperienced Stata users. `eventstudy2` is the most complete command and provides comprehensive data management routines, hypothesis testing, and output. `estudy` is a useful command for studies with a limited number of events and/or if the researcher is interested in assessing the statistical significance of abnormal returns around the individual events. `estudy` is the only command that provides export routines to spreadsheet software and LaTeX.

3 Applicability to event studies in leading field journals

To substantiate my analysis of the usefulness of the three community-contributed event study commands, I collect and analyze all studies that appeared between 2009 and 2018 in the Journal of Finance, Journal of Accounting Research, and Management Science, and which apply the event study method as either their main method of analysis or as a tool to calculate abnormal returns for other purposes, e.g., control variables.[1] The analysis in total comprises 180 articles, thereof 55 in the Journal of Accounting Research (17.5% of all articles that appeared in this Journal during that period), 71 in the Journal of Finance (10.1%), and 54 in Management Science (3.0%). Thus, the event study design can be considered one of most prominent research methods in the journals' domains.

1. The full data set on which the following analyses are based is displayed in Tables 5a to 5d in the appendix.

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To assess the level of applicability of the three community-contributed commands, I evaluate them against the journal articles across two dimensions: the benchmark model that has been used in the study to calculate abnormal returns and the test statistics that have been used. If a community-contributed command supports all benchmark models and all calculations of test statistics that are applied in a journal article, I classify its level of applicability as “fully applicable” with respect to that study. If a command supports at least one of the applied benchmark models and at least one test statistic, I classify its level of applicability as “partially applicable”. If the command is neither fully nor partially applicable, I classify it as “not applicable” with respect to that study.

The command `eventstudy` could have been used in 8.33% (fully applicable) and 2.22% (partially applicable) of all articles, which are the studies that do not test abnormal returns for statistical significance and use the market model or the constant mean return model.[2]. `eventstudy2` has the highest levels of applicability with 90.56% (fully applicable) and 2.78% (partially applicable). `estudy` ranges between the two other commands with 58.33% (fully applicable) and 9.44% (partially applicable). This analysis does not consider any restrictions with respect to the maximum number of events (11 000 for `eventstudy` and 24 000 for `estudy` in Stata MP) and is thus biased in favor of `eventstudy` and `estudy`.

Some further descriptive statistics of the journal articles are of interest to evaluate how convenient the community-contributed commands are. `eventstudy`’s and `eventstudy2`’s data inputs are organized in long rather than wide format. The long format is also the format of the most common share price databases, CRSP, Compustat and CSMAR, which are used by about 93% of the studies.

4 Practical limitations

4.1 Run time

Run time can represent a material constraint in applying event study commands. To compare the three community-contributed commands, I create sample datasets by extracting return data from CRSP for the period 2005–2014. I randomly assign one event date per firm and ensure that all return data is available during the estimation window beginning 249 and ending 11 trading days before the event date as well as during the event window ranging from 10 trading days before to 10 trading days after the event. On the event date, I add 0.05 to the return variable in order to simulate an event causing an abnormal return of 5%. Further, I add a randomly generated[3] market index return variable. To simulate run time, I randomly select subsamples between 50 and 2,050 events, in steps of 100, and six larger samples of 5 000, 10 000, 30 000, 60 000, 90 000 and 120 000 events. I use Stata16 MP4 on an Intel Xeon Gold 6126 CPU with 2.60 GHz, 2 sockets, 24 cores and 48 logical processors. Nevertheless, since Stata16 MP will use

2. `eventstudy` is restricted to the market model but setting all market returns to zero provides results which are equivalent to those for the constant mean return model.
3. I use the function `uniform` and divide by 20 to obtain a reasonable return distribution.

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Table 3: Applicability of community-contributed event study commands.

	eventstudy		eventstudy2		estudy	
Panel A: All three journals						
Fully applicable	15	8.33%	163	90.56%	105	58.33%
Partially applicable	4	2.22%	5	2.78%	17	9.44%
Not applicable	161	89.44%	12	6.67%	58	32.22%
Panel B: Journal of Accounting Research						
Fully applicable	3	5.45%	54	98.18%	32	58.18%
Partially applicable	1	1.82%	0	0.00%	5	9.09%
Not applicable	51	92.73%	1	1.82%	18	32.73%
Panel C: Journal of Finance						
Fully applicable	6	8.45%	65	91.55%	46	64.79%
Partially applicable	2	2.82%	1	1.41%	3	4.22%
Not applicable	63	88.73%	5	7.04%	22	30.99%
Panel D: Management Science						
Fully applicable	6	11.11%	44	81.48%	27	50.00%
Partially applicable	1	1.85%	4	5.63%	9	16.67%
Not applicable	47	87.04%	6	8.45%	18	33.33%

The information in this table is based on 180 articles published in the three journals between 2009 and 2018. The benchmark models and test statistics that are applied in these studies (see Tables 5a to 5d in the appendix) are then mapped to the features of community-contributed event study commands displayed in Table 2. If a command supports all benchmark models, all calculations of test statistics that are applied in a journal article, and the required data management tasks, its level of applicability is defined as "fully applicable" with respect to that study. If a command supports at least one of the applied benchmark models, at least one test statistic, and the required data management tasks, its level of applicability is defined as "partially applicable". If the command is neither fully nor partially applicable, it is defined as "not applicable".

a maximum of 4 logical processors, the run times are not expected to differ materially from that on common desktop PCs. However, for testing `eventstudy2` with the parallel option, I use 40 logical processors, which resembles run times on a high performance computing cluster.

When comparing run times across community-contributed commands, it is important to recall some of their conceptual differences. First of all, `eventstudy` does not calculate any test statistics, which is why it is generally expected to be the fastest command in all scenarios. `eventstudy2` calculates and reports all available test statistics during every run and provides extensive data management capabilities. `estudy`, on the other hand only provides one test statistic per run but provides it for each event firm separately. Thus, the prediction of run time for `eventstudy2` compared to `estudy` is less clear. The left graph in Figure 1 plots the run times for `eventstudy2`, `eventstudy2` with the `parallel` option, and `estudy` against the numbers of events. `estudy` is run

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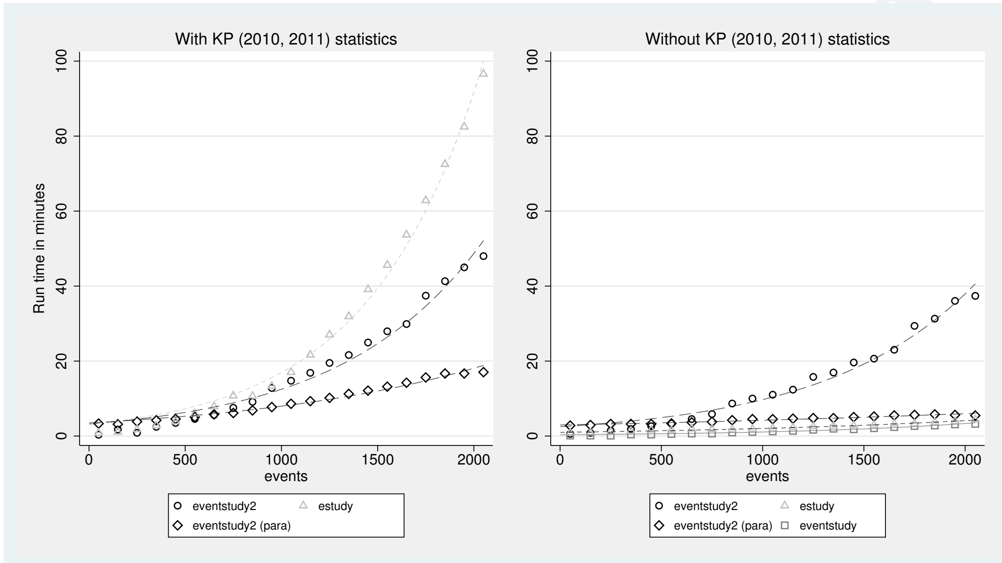

Figure 1: Execution times of event studies with 50 to 2 050 events.

with the `diagnosticsstat(KP)` option and `eventstudy2`'s option `nokolari` is not enabled, which in both instances triggers the calculation of the most calculation-intense Kolari and Pynnonen (2010, 2011) (KP) statistics. The graphs point towards an exponential growth of run time with a considerably higher growth rate for `estudy`. While `eventstudy2` can execute event studies with 2 000 events in less than an hour, the run time for `estudy` approaches 100 minutes.[4] Further, the graph clearly demonstrates the benefits of the `parallel` option of `eventstudy2`, which already breaks even at around 700 events and is associated with a much lower growth rate. An event study with 2 000 events can be calculated in less than 20 minutes.

The right graph in Figure 1 shows the run time when `estudy` is run with the `diagnosticsstat(Norm)` and `eventstudy2` with the `nokolari` option, which suppress the calculation of the Kolari and Pynnonen (2010, 2011) statistics. It also shows the run time of `eventstudy`, which does not provide any test statistics. The growth rate for `estudy` drops substantially, which demonstrates that much of the priorly observed sensitivity of the run time to the number of events is attributable to computing the Kolari and Pynnonen (2010) statistic. However, `eventstudy2`'s run time depends less on test statistics, which are fully implemented in Mata, but is largely driven by its comprehensive data management routines (e.g., implementing the Maynes and Rumsey (1993) algorithm for handling thinly traded stocks) and reporting routines (reporting

4. The Kolari and Pynnonen (2010, 2011) statistics require calculation of all pairwise correlations between abnormal returns of event firms, which becomes an exponentially intense task with an increasing number of events for both `eventstudy2` and `estudy`. However, `estudy`'s feature to calculate test statistics for each event firm should not put it at an undue disadvantage, if programmed efficiently, since cross-correlations do not matter in single event firm settings.

which events had to be dropped and for which reason).

As I demonstrated in my analysis of published event studies in Section 3, most event studies comprise more than only a few thousand events. Therefore, I record the run time in hours of the three community-contributed commands for studies with samples of 5 000, 10 000, 30 000, 60 000, 90 000 and 120 000 events, if feasible, in Table 4. I measure run times with and without the calculation of the Kolari and Pynnonen (2010, 2011) statistics (as in Figure 1).

Table 4: Run time in hours of community-contributed event study commands.

	`eventstudy`	
Events	No test statistics available	
5000	0.3	
10,000	1.0	
>11,000	`eventstudy` hits the matsize limit of 11,000.	
	`eventstudy2`	
Events	With KP (2010, 2011) statistics	Without KP (2010, 2011) statistics
5000	4.7	3.6
10,000	19.6	14.9
15,000	43.1	31.5
30,000	169.5	129.2
>30,000	Feasible but strong exponential growth.	
	`eventstudy2, parallel`	
Events	With KP (2010, 2011) statistics	Without KP (2010, 2011) statistics
5000	1.4	0.2
10,000	4.9	0.4
15,000	11.5	0.5
30,000	45.2	1.0
60,000	Feasible but	2.5
90,000	strong exponential growth	4.4
120,000	...	6.6
>120,000	...	Feasible.
	`estudy`	
Events	With KP (2010, 2011) statistics	Without KP (2010, 2011) statistics
5000	26.6	0.4
10,000	250.9	2.1
15,000	>24 days	5.7
23,000	>50 days	20.2
>24,000	`estudy` hits the maxiumum variables limit of 120,000.	

Most notably, my tests reveal that `eventstudy` hits Stata16 MP's matsize limit of 11 000 when asked to calculate an event study with 11 000 or more events. `estudy` hits the maximum number of variables limit of 120 000 if asked to calculate event studies with 24 000 or more events. Further, the run time of `estudy` increases drastically for

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larger samples when it asked to calculate the Kolari and Pynnonen (2010, 2011) statistics. 250.9 hours for a study with only 10 000 events will most likely be considered impracticable by most researchers. `eventstudy2` is able to perform this task in 19.6 hours (4.9 hours in parallel computing mode) due to the fact that it loads the abnormal return matrices fully into Mata and calculates cross-correlations there, which is much more computationally efficient than correlating Stata variables.[5] Although `estudy` is theoretically able to run larger event studies with the Kolari and Pynnonen (2010, 2011) statistics, I was not able to obtain results for the 15 000 events sample after 24 days of uninterrupted calculation. However, an analysis of the time that `estudy` requires to calculate the cross-correlation of one event's abnormal returns with all other events' abnormal returns during the estimation windows allows me estimate a lower boundary for the 23 000 events sample, which is at least 50 days of run time.

Without being asked to calculate Kolari and Pynnonen (2010, 2011) statistics, `estudy` is considerably faster than `eventstudy2`. However, `eventstudy2` retakes the lead if run in parallel computing mode on 40 cores.

To conclude on the issue of run time, `eventstudy` and `estudy` are not suitable to run bigger event studies due to their handling of Stata16 MP's limits. If the user is interested in obtaining Kolari and Pynnonen (2010, 2011) statistics, the practical limits of `estudy` kick in much earlier than the theoretically feasible 23 000 events.

4.2 Consistency of results and thin trading

While calculation times, as demonstrated in the previous subsection, differ substantially across the three community-contributed event study commands, the abnormal returns and test statistics they calculate should be consistent. To test this presumption, I use the previously described setting with 100 randomly selected event samples and repeat the analysis 100 times, each time using each of the three commands on the selected sample. I calculate (cumulative) average abnormal returns for days [0], [1], [0;1] and [-1;1] as well as the Kolari and Pynnonen (2010) statistics when using `eventstudy2` and `estudy`. Untabulated results show that all metrics exhibit almost perfect correlation across commands, which implies consistency in this ideal setting where no return data are missing.

However, in real world settings, researchers commonly have to handle stock return data when stocks trade infrequently (thin trading). Let us assume the following scenario: A stock has a continuously compounded abnormal return of -2% on the event day [0] and +2% on the day after the event day [+1]. On the event day, however, the stock is not traded, which means that its abnormal return is not observable. The day after the event day, when the stock resumes trading, the observable abnormal return will be zero because the closing price on this day will match the closing price on the day before the event day [-1]. How should an event study program handle such situations? Ideally, it recognizes that the return observed on day [+1] is a cumulated return and

5. `estudy` stores cross-correlations in Mata but calculates them in Stata using the `correlate` command.

excludes it from the calculation of the abnormal return on day [+1]. Nevertheless, it should include this return observation in the calculation of the cumulative average abnormal returns, CAAR[0;1]. Further, the missing return on day [0] should not be set to zero but excluded from the calculation of the average abnormal event day return, AAR[0]. `eventstudy2` follows these rules by implementing the Maynes and Rumsey (1993) algorithm for the handling of trade-to-trade returns and thinly traded stocks. The help files of `eventstudy` and `estudy` do not explain how the commands deal with this issue.

To get a better understanding of the ability of three community-contributed commands to handle thin trading, I artificially and randomly define half of the event day [0] returns as thinly traded, which means that the return is compounded into the following day [+1] before being set to missing. Before introducing thin trading, I add a random return to the return on day [0] and subtract the same return on day [+1]. Thus, we know the true AAR[0] and AAR[+1] as well as that the CAAR[0;+1] and CAAR[-1;+1] are truly zero. Again, I perform 100 runs of 100 randomly selected samples using each of the three community-contributed event study commands.

The upper left graph in Figure 4.2 shows plots of measured average abnormal event day [0] returns on artificially induced abnormal returns. All three commands provide estimates that are close to the ideal 45°-line through the origin and are thus unbiased. Thus, none of the three commands erroneously attributes a zero return to the missing return observations that result from thin- or non-trading. However, the results differ with respect to day [+1] (upper right graph), where `estudy` and `eventstudy` systemically underestimate the return reversal because they attribute some of the abnormal event day returns to day [+1]. Only `eventstudy2` realizes that about half of the day [+1] returns are confounded with day [0], at that time unobservable, returns.

The lower left graph in Figure 4.2 demonstrates that this error is mitigated in the calculating of CAAR[0;1] by `eventstudy` by first calculating CARs by event firm and across time, and then averaging them across event firms (the latter has to be performed by the user). `estudy`, however, appears to first calculate AARs by time and across events, and then averages them across time, which entertains the bias and creates an overestimation in terms of the absolute value of CAAR[0;1], which in my simulation is zero by construction. In my simulation of perfect abnormal return reversal within one trading day, the bias is linearly related to the fraction of thinly traded stocks (50% in my simulation) and the induced abnormal return. For instance, one can see that if half of event day returns suffer from thin trading and the induced abnormal return is 5%, `estudy` overestimates CAAR[0;+1] by about 2.5 percentage points. As can be seen from the graph in lower right, the bias does not get weaker if the window is extended to three days, i.e., CAAR[-1;+1].

To conclude, all three commands provide consistent results if thin trading is not present. If, however, thin trading is an issue and the return data are trade-to-trade returns, only `eventstudy2` provides unbiased results.

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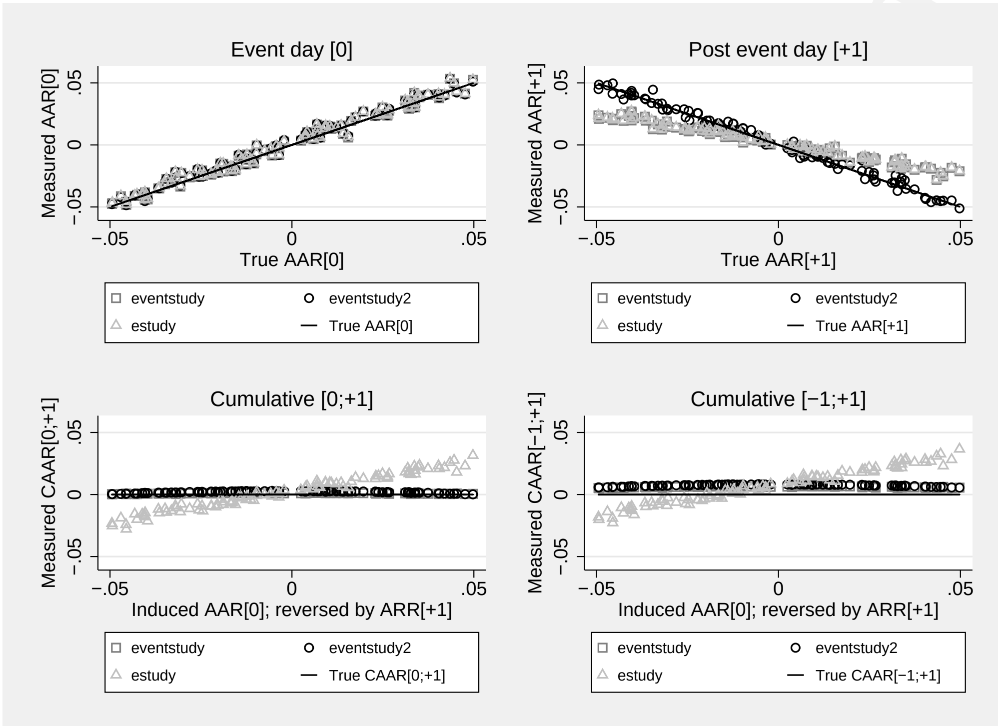

Figure 2: Cumulative average abnormal return calculation with thin trading on the event day.

5 Conclusion

All three commands discussed in this paper, `eventstudy`, `eventstudy2` and `estudy`, are useful in conducting event studies as they are commonly performed in the accounting, finance and management literature. In terms of completeness as I define it, i.e., availability of test statistics and benchmark models, handling of thin trading and reporting on dropped observations, my command `eventstudy2` surpasses its alternatives. However, the other commands have superior input (`eventstudy`) or output (`estudy`) routines, which might make them the better choice for users who are operating with smaller samples and/or do not require complex test statistics. The `estudy` command might be particularly suited for analyses of data that comes from Datastream as opposed to WRDS, since data that is extracted with Datastream request tables typically comes in wide rather than long format. The user should ensure, though, that their sample firms do not suffer from thin trading and that the sample is sufficiently small. Overall, it can be stated that, given the three available community-contributed commands, there is no need for Stata users to leave their preferred programming environment to conduct event studies.

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Finally, since I am often asked about that via e-mail or most recently at the Stata Conference 2020, I would like to briefly explain the differences between the three community-contributed commands and the Stata code that is offered at the Princeton University website[6]. The Princeton code is a very useful starting point for writing one's own event study code because it provides a good overview on how to initially organize the data. However, it does not provide any advanced hypothesis testing or input/output routines. Developing an event study program takes years of intense work. `estudy.ado` has more than 1,400 and `eventstudy2.ado` more than 1,700 lines of code, and although the amount of code does not necessarily predict the quality of program, it can provide a hint to its complexity and thus functionality. If at all, the roughly 40 lines of code on the Princeton website are comparable, in terms of functionality, to the `eventstudy` but not the other two commands.

Acknowledgments

I thank Joe Newton (the editor) and an anonymous referee for their valuable contributions. I also thank the attendees of the 2020 Stata Conference and all users whose feedback has substantially improved this article and the `eventstudy2` command.

Appendix: Event studies in three leading field journals published during the period 2009–2018.

6. https://dss.princeton.edu/online_help/stats_packages/stata/eventstudy.html

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Table 5a: Studies using the event study method.

Authors	Sample period	Datasources	Benchmark models	Test statistics	Events
Abarbanell and Park (2017)	1993–2012	CRSP	BH_MATCH	t-Stat	47,977
Abrahamson et al. (2011)	1998–2007	CRSP	MA	None	2,788
Agarwal et al. (2013)	2004–2007	CRSP	MM	Patell Z, GenSign	66
Agarwal et al. (2016)	1998–2010	CRSP	MA	None	3,046
Aggarwal et al. (2015)	2007–2009	CRSP	RAW	None	3,053
kenneth R. Ahern and Harford (2014)	1986–2010	CRSP	MA	None	not reported
Akbas (2016)	1980–2011	CRSP	MA	None	366,454
Albuquerque and Schroth (2015)	1990–2010	CRSP	RAW	None	114
Allee and DeAngelis (2015)	2004–2014	CRSP	MA, FM	None	33,428
Ammann et al. (2016)	1992–2008	CRSP	MM	t-Stat	1,875
Anderson et al. (2012)	2005–2007	CRSP	PEA	t-Stat	1,571
Anderson et al. (2018)	1992–2014	CRSP	RAW	None	27,615
Arikan and Stulz (2016)	1975–2008	CRSP	MA	t-Stat, Wilcoxon	3,081
Ashbaugh-Skaife et al. (2009)	2003–2005	CRSP	BH_IND	Wilcoxon	787
Babenko (2009)	1996–2002	CRSP	MM	None	1,174
Badoer and James (2016)	2001–2001	CRSP Treasury	COMEAN	t-Stat	1
Becher et al. (2015)	1993–2008	CRSP	RAW, CAL	None, t-Stat	5,381
Berkman and Truong (2009)	2000–2004	CRSP, yahoo!Finance	BA	t-Stat	38,031
Berkman et al. (2014)	1999–2010	Compustat Global	MA	t-Stat	4,136
Bernhardt et al. (2016)	2003–2010	CRSP	BH_IND	t-Stat	24,793
Betton et al. (2014)	1980–2008	CRSP	MM	None	6,150
Bhojraj et al. (2009)	1988–2006	CRSP	MA, BH_MATCH, CAL	t-Stat, BS t-Stat	35,530
Blankespoor et al. (2017)	2011–2013	CRSP	BH_MATCH	None	224
Bradley et al. (2017)	1983–2011	CRSP	MA	None	40,719
Brennan et al. (2016)	1983–2010	CRSP	MA	None	not reported
Brown and Tucker (2011)	1997–2006	CRSP	MA	None	23,487
Bruno et al. (2016)	1999–2003	CRSP	BH_MATCH	t-Stat	2,002
Bushee et al. (2010)	1993–2004	CRSP	MA	None	27,987
Bushee et al. (2011)	1999–2007	CRSP	BH_MATCH	t-Stat, Wilcoxon	95,105
Bushman et al. (2017)	2000–2012	CRSP	MA	None	41,760
Call et al. (2018)	1978–2012	CRSP	MA	None	658
Cao and Narayanamoorthy (2012)	1987–2008	CRSP	BH_IND	None	305,908
Cao et al. (2015)	2000–2010	CRSP	BH_IND, PEA	None	40,807
Cen et al. (2016)	1979–1995	CRSP	BH_MATCH	None	62,041
Chang et al. (2010)	1992–2002	CRSP	MM, FM, BH_IND, BH_MATCH	t-Stat, Wilcoxon	298
Chava et al. (2018)	1989–2007	CRSP	MM	None	1,677
Cheong and Thomas (2018)	1993–2013	CRSP	MA	None	197,004
Chhaochharia et al. (2017)	1999–2006	CRSP	MM	None	6,643
Choudhary et al. (2009)	2004–2005	CRSP	MM	t-Stat	365
Christensen et al. (2009)	2004–2004	CRSP	MA	None	136
Cohen and Schmidt (2009)	1993–2003	CRSP	MA	None	266,520
Cohn et al. (2016)	2010–2010	CRSP	COMEAN	CDA	3
Collin-Dufresne and Fos (2015)	1994–2010	CRSP	BH_IND	t-Stat	3,126
Crane and Koch (2018)	1980–2012	CRSP	MA	None	26,766

Benchmark models are raw returns (RAW), the constant mean return model (COMEAN) (MacKinlay 1997, p. 17), the market-adjusted return model (MA), returns adjusted against a benchmark which is not the market index (BA), the market model (MM) (MacKinlay 1997, p. 18), a multiple-factor model (FM) (e.g., Peress 2010, Fn. 27), buy-and-hold abnormal returns against a single market index (BH_IND) (e.g., Ashbaugh-Skaife et al. 2009, p. 32), buy-and-hold abnormal returns against an individual benchmark (BH_MATCH), e.g., matched portfolio returns (e.g., Lyon et al. 1999, p. 167–173), the calendar portfolio approach (CAL) (e.g., Lyon et al. 1999, p. 192–197), the event parameter approach (EP), the capital asset pricing model (CAPM) (MacKinlay 1997, p. 19), the returns across time and securities model (IRATS) (Ibbotson 1975), the post-event alpha estimation (PEA) (e.g., Anderson et al. 2012, p. 375), beta-adjusted buy-and-hold abnormal returns (Dellavigna and Pollet 2009, p. 721), and "unknown", which means that the author(s) do(es) not report which benchmark model they use. Test statistics are simple cross-sectional or time-series t-tests of whether abnormal returns are different from zero (t-Stat), the crude dependence adjustment (CDA) (Brown and Warner 1980, pp. 223, 253), the (Patell 1976, p. 254–258) test (Patell Z), the Boehmer et al. (1991, pp. 258–270) test of standardized residuals corrected for event-induced changes in volatility (BMP), the Kolari and Pynnonen (2010, p. 4003) test of standardized residuals corrected for event-induced changes in volatility and cross-correlation (KP), the Corrado (1989, pp. 387–388) rank test or the Corrado and Zivney (1992, pp. 345-346) rank test corrected for event-induced volatility of rankings (Corrado), the generalized sign test according to Cowan (1992, pp. 345–346), the Wilcoxon (1945) signed-ranks test, and bootstrapped versions of the t-test (e.g., Lyon et al. 1999, pp. 173–175).

Table 5b: Studies using the event study method.

Authors	Sample period	Datasources	Benchmark models	Test statistics	Events
Crawford et al. (2018)	2008–2010	CRSP	MM, FM	t-Stat, CDA	1,751
Cready and Gurun (2010)	1973–2006	CRSP	RAW	t-Stat	8,312
Cready et al. (2014)	2003–2010	CRSP	BA	None	11,683
Cuñat et al. (2012)	1997–2007	CRSP	FM	t-Stat	2,377
Da et al. (2011)	2004–2007	CRSP	BH_MATCH	None	185
de Bodt et al. (2018)	1990–2014	CRSP, Datastream	MM	None	5,148
De Franco et al. (2009)	2002–2005	TRACE/FSID	MA	t-Stat	13,811
DeHaan et al. (2017)	1990–2013	CRSP	BH_MATCH	None	193,109
Dellavigna and Pollet (2009)	1984–2006	CRSP	BH_BETA	None	49,537
Demerjian et al. (2012)	1992–2009	CRSP	RAW	t-Stat	2,229
Dimitrov and Jain (2011)	1996–2005	CRSP	BA	t-Stat	26,408
Doidge et al. (2010)	2002–2008	CRSP	MM	CDA, GenSign	137
Doidge and Dyck (2015)	2006–2006	Datastream	EP	t-Stat	149
Donelson and Hopkins (2016)	1996–2007	CRSP	MA	None	175,129
Døskeland and Hvide (2011)	1994–2005	OSE	BH_MATCH, CAL	BS returns	116
Doyle and Magilke (2013)	2004–2007	CRSP	BH_MATCH	None	1,172
Drake et al. (2012)	2005–2008	CRSP	BH_MATCH	t-Stat	4,139
Durnev and Mangen (2009)	1997–2002	CRSP	MA	Patell Z, GenSign	67,443
Dyck et al. (2010)	1996–2004	CRSP	EP	t-Stat	216
Dyreng et al. (2016)	2011–2011	Compustat Global	BH_IND	BS t-Stat	1,520
Edmans et al. (2012)	1980–2007	CRSP	MA	None	6,555
Engelberg et al. (2012)	2005–2009	CRSP	BA	None	826
Ertimur et al. (2013)	2010–2011	CRSP	MA, FM, BH_MATCH	t-Stat, Wilcoxon	1,195
Falato et al. (2015)	1993–2005	CRSP	MM	None	1,771
Fang et al. (2016)	2005–2007	CRSP	BH_IND	t-Stat	<3,000
Fang et al. (2017)	1997–2006	CRSP	MA	None	5,702
Fernando et al. (2012)	2008–2008	CRSP	FM	KP	946
Firth et al. (2013)	2004–2008	CRSP	MA, MM, BH_MATCH	t-Stat	29,505
Flammer (2015)	1997–2012	CRSP	MM, FM	None	1,845
Fosfuri and Giarratana (2009)	1999–2003	yahoo!Finance	EP	t-Stat	115
Fracassi and Tate (2012)	2000–2007	CRSP	MM	None	3,863
Franco et al. (2017)	1999–2009	CRSP	BH_IND, BH_MATCH	t-Stat	28,536
Fu and Huang (2016)	1984–2012	CRSP	BH_MATCH, CAL, IRATS	t-Stat	14,309
Fung et al. (2014)	1993–2007	CSMAR	RAW	None	321
Gande and Saunders (2012)	1999–2009	CRSP	MA	Patell Z	323
Garfinkel (2009)	2002–2002	CRSP	MM	None	13,017
Giannetti et al. (2015)	1999–2009	CSMAR	MA	None	185
Gilje and Taillard (2016)	2003–2010	CRSP	MM	Patell Z	167
Gillan et al. (2009)	2000–2000	CRSP	BH_IND	None	494
Goldman and Huang (2015)	1993–2007	CRSP	MA	t-Stat	287
Golubov et al. (2012)	1996–2009	CRSP	MM	None	3,995
Gorton et al. (2009)	1985–1999	CRSP	MA	None	1,334
Green and Hwang (2012)	1975–2008	CRSP	BH_MATCH	None	7,975
Gurun et al. (2016)	2002–2004	CRSP	RAW	t-Stat	1,100
Hail et al. (2014)	1993–2008	Datastream	MA	None	222,766

Benchmark models are raw returns (RAW), the constant mean return model (COMEAN) (MacKinlay 1997, p. 17), the market-adjusted return model (MA), returns adjusted against a benchmark which is not the market index (BA), the market model (MM) (MacKinlay 1997, p. 18), a multiple-factor model (FM) (e.g., Peress 2010, Fn. 27), buy-and-hold abnormal returns against a single market index (BH_IND) (e.g., Ashbaugh-Skaife et al. 2009, p. 32), buy-and-hold abnormal returns against an individual benchmark (BH_MATCH), e.g., matched portfolio returns (e.g., Lyon et al. 1999, p. 167–173), the calendar portfolio approach (CAL) (e.g., Lyon et al. 1999, p. 192–197), the event parameter approach (EP), the capital asset pricing model (CAPM) (MacKinlay 1997, p. 19), the returns across time and securities model (IRATS) (Ibbotson 1975), the post-event alpha estimation (PEA) (e.g., Anderson et al. 2012, p. 375), beta-adjusted buy-and-hold abnormal returns (Dellavigna and Pollet 2009, p. 721), and "unknown", which means that the author(s) do(es) not report which benchmark model they use. Test statistics are simple cross-sectional or time-series t-tests of whether abnormal returns are different from zero (t-Stat), the crude dependence adjustment (CDA) (Brown and Warner 1980, pp. 223, 253), the (Patell 1976, p. 254–258) test (Patell Z), the Boehmer et al. (1991, pp. 258–270) test of standardized residuals corrected for event-induced changes in volatility (BMP), the Kolari and Pynnonen (2010, p. 4003) test of standardized residuals corrected for event-induced changes in volatility and cross-correlation (KP), the Corrado (1989, pp. 387–388) rank test or the Corrado and Zivney (1992, pp. 345-346) rank test corrected for event-induced volatility of rankings (Corrado), the generalized sign test according to Cowan (1992, pp. 345–346), the Wilcoxon (1945) signed-ranks test, and bootstrapped versions of the t-test (e.g., Lyon et al. 1999, pp. 173–175).

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Table 5c: Studies using the event study method.

Authors	Sample period	Datasources	Benchmark models	Test statistics	Events
Hartzmark and Shue (2018)	1984–2013	CRSP	BH_MATCH	None	75,897
Hendershott and Madhavan (2015)	2010–2011	CRSP	RAW	None	11,122
Henry and Koski (2017)	1999–2007	CRSP	MM	t-Stat	24,741
Hilary et al. (2014)	2002–2010	CRSP	MA, BH_MATCH	None	6,813
Hirshleifer et al. (2009)	1995–2004	CRSP	BH_MATCH	None	112,839
Hobson et al. (2012)	2007–2007	CRSP	MA	None	111
Hsu et al. (2010)	1980–2001	CRSP	MM	Patell Z	4,188
Huang et al. (2018)	2003–2012	CRSP	MA	None	17,733
Huang and Hilary (2018)	1998–2010	CRSP	MM	Wilcoxon	78
Hui and Yeung (2013)	2004–2008	CRSP	BH_MATCH	t-Stat	25,195
Hutton et al. (2015)	1993–2007	CRSP	MM, FM	t-Stat	34,318
Iliev (2010)	2002–2005	CRSP	FM	t-Stat	10
Jagolinzer (2009)	2000–2005	CRSP	MA, BH_IND	t-Stat	30,924
Jagolinzer et al. (2011)	2006–2007	CRSP	PEA	t-Stat	260
Jame et al. (2016)	2012–2013	CRSP	BH_MATCH	None	3,429
Jenter et al. (2011)	1991–2004	CRSP	RAW, MA, BA	t-Stat	651
Jenter and Lewellen (2015)	1989–2007	CRSP	MA	None	2,801
Jiang et al. (2012)	1996–2007	CRSP, Datastream, Bloomberg	MA	None	277
Jiang et al. (2018)	2000–2015	CRSP	FM	t-Stat, Wilcoxon	255
Jin et al. (2012)	1996–2010	CRSP	BH_MATCH	None	71,482
Johnson and So (2018)	1993–2012	CRSP	MA	t-Stat	12,472
Jorion and Zhang (2009)	1999–2005	CRSP	MM	CDA	251
Kadyrzhanova and Rhodes-Kropf (2011)	1990–2006	CRSP	MM	None	872
Kahl et al. (2015)	1991–2008	CRSP	MM	t-Stat, GenSign	3,325
Kalaignanam et al. (2013)	1996–2006	CRSP	FM	BMP	158
Kaniel et al. (2012)	2000–2003	CRSP	MA	t-Stat	17,564
Karolyi and Taboada (2015)	1995–2012	CRSP	MM	t-Stat	3,307
Karolyi (2018)	1994–2012	CRSP	MM, MA	None	9,458
Karpoff and Lou (2010)	1988–2005	CRSP	MA	t-Stat	454
Kecskés et al. (2017)	1994–2010	CRSP	BH_MATCH	None	65,523
Keung et al. (2010)	1992–2006	CRSP	MM	None	139,885
Kim and Song (2015)	1996–2009	CRSP	EP	t-Stat	3,841,786
Klein and Zur (2009)	1995–2005	CRSP	BH_MATCH	t-Stat, Wilcoxon	139
Knittel and Stango (2014)	2009–2009	CRSP	EP	GenSign, Wilcoxon	1
Koester et al. (2016)	1998–2007	CRSP	BH_IND	None	44,525
Kolasinski et al. (2013)	2003–2007	CRSP	BH_IND	None	586,435
Kothari et al. (2009)	1962–2004	CRSP	MA	None	5,803
Krüeger et al. (2015)	1992–2007	CRSP	MA	None	6,366
Kumar (2010)	1983–2005	CRSP	MA	None	1,953,481
Kutsuna et al. (2009)	1997–2003	JASDAQ	BH_IND	None	487
Lee et al. (2015)	2000–2012	CRSP	MA	t-Stat	405
Lee and Lo (2016)	1994–2008	CRSP	MA	None	112,564
Lemmon et al. (2014)	1996–2009	CRSP	MM	CDA	231
Leung and Veenman (2018)	2006–2014	CRSP	BH_MATCH	None	6,417
Levi et al. (2010)	1997–2007	CRSP	MM, MM	None	357

Benchmark models are raw returns (RAW), the constant mean return model (COMEAN) (MacKinlay 1997, p. 17), the market-adjusted return model (MA), returns adjusted against a benchmark which is not the market index (BA), the market model (MM) (MacKinlay 1997, p. 18), a multiple-factor model (FM) (e.g., Peress 2010, Fn. 27), buy-and-hold abnormal returns against a single market index (BH_IND) (e.g., Ashbaugh-Skaife et al. 2009, p. 32), buy-and-hold abnormal returns against an individual benchmark (BH_MATCH), e.g., matched portfolio returns (e.g., Lyon et al. 1999, p. 167–173), the calendar portfolio approach (CAL) (e.g., Lyon et al. 1999, p. 192–197), the event parameter approach (EP), the capital asset pricing model (CAPM) (MacKinlay 1997, p. 19), the returns across time and securities model (IRATS) (Ibbotson 1975), the post-event alpha estimation (PEA) (e.g., Anderson et al. 2012, p. 375), beta-adjusted buy-and-hold abnormal returns (Dellavigna and Pollet 2009, p. 721), and "unknown", which means that the author(s) do(es) not report which benchmark model they use. Test statistics are simple cross-sectional or time-series t-tests of whether abnormal returns are different from zero (t-Stat), the crude dependence adjustment (CDA) (Brown and Warner 1980, pp. 223, 253), the (Patell 1976, p. 254–258) test (Patell Z), the Boehmer et al. (1991, pp. 258–270) test of standardized residuals corrected for event-induced changes in volatility (BMP), the Kolari and Pynnonen (2010, p. 4003) test of standardized residuals corrected for event-induced changes in volatility and cross-correlation (KP), the Corrado (1989, pp. 387–388) rank test or the Corrado and Zivney (1992, pp. 345-346) rank test corrected for event-induced volatility of rankings (Corrado), the generalized sign test according to Cowan (1992, pp. 345–346), the Wilcoxon (1945) signed-ranks test, and bootstrapped versions of the t-test (e.g., Lyon et al. 1999, pp. 173–175).

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Table 5d: Studies using the event study method.

Authors	Sample period	Datasources	Benchmark models	Test statistics	Events
Levi and Zhang (2015)	1993–2009	CRSP	EP	t-Stat	109,547
Li and Zhang (2015)	2004–2005	CRSP	MA	None	1,622
Loh and Stulz (2018)	1990–2014	CRSP	BA	None	71,070
Loughran and Mcdonald (2011)	1994–2008	CRSP	BH_IND	None	50,115
Loughran and Mcdonald (2014)	1994–2011	CRSP	BH_IND	None	28,434
Louis and Sun (2010)	1994–2006	CRSP	MA, BH_MATCH	t-Stat	1,923
Louis et al. (2013)	1995–2006	CRSP	MA	None	4,492
Loureiro and Taboada (2015)	1990–2012	Datastream	MM	None	9,844
Lui et al. (2012)	2000–2006	CRSP	MA	t-Stat, Wilcoxon	12,394
Madsen (2017)	1990–2014	CRSP	MA	None	33,740
Manchiraju and Rajgopal (2017)	2009–2013	CMIE	MM	Wilcoxon	556
Manconi et al. (2018)	2002–2009	CRSP	BH_MATCH	None	71,623
Martin and Shalev (2017)	1980–2012	CRSP	MM	None	2,138
Masulis et al. (2009)	1994–2002	CRSP	MM	None	410
Masulis and Mobbs (2011)	1997–2006	CRSP	MM	t-Stat, Wilcoxon	118
Mayew and Venkatachalam (2012)	2007–2007	CRSP	BA	None	1,647
McNally et al. (2017)	2004–2006	TSX	BH_MATCH	t-Stat	3,761
Michels (2017)	1994–2012	CRSP	BH_IND	t-Stat	78
Milian (2015)	1996–2010	CRSP	MA	None	76,462
Nguyen and Nielsen (2014)	1991–2008	CRSP	MM, FM	Patell Z, Wilcoxon	149
Oxley et al. (2009)	1994–2004	CRSP, Datastream	MM, MM	t-Stat	8,918
Peress (2010)	1996–2005	CRSP	FM	None	28,172
Qian and Zhu (2018)	1980–2013	CRSP	CAPM	None	3,533
Rajamani et al. (2017)	1990–2005	Datastream	MM	t-Stat, Patell Z	571
Ransbotham and Mitra (2010)	1995–2001	CRSP	MA, MM, FM	Patell Z, GenSign	140
Robinson et al. (2015)	1996–2006	CRSP	FM	CDA, Corrado, BS returns	171
Ryngaert and Thomas (2012)	1996–2006	CRSP	MM	GenSign	421
Savor and Lu (2009)	1978–2003	CRSP	BH_MATCH	None	1,050
Savor and Wilson (2016)	1974–2012	CRSP	MA	None	626,567
Serfling (2016)	1977–1998	CRSP	MM, FM	t-Stat	12
Servaes and Tamayo (2014)	1983–2005	CRSP	MA	t-Stat, GenSign	2,450
Seybert and Yang (2012)	1996–2006	CRSP	MA, MA	None	31,360
Sheen (2014)	1980–2009	CRSP	MA	t-Stat	38
Shenoy (2012)	1981–2004	CRSP	MM	Patell Z, GenSign	114
Shon and Veliotis (2013)	2003–2010	CRSP	MA	None	16,214
Shroff et al. (2013)	2003–2008	CRSP	MA	None	1,484
Silvers (2016)	1995–2010	Datastream	FM	t-Stat	28
Solomon (2012)	2002–2007	CRSP	BH_MATCH	None	340,928
Spiegel and Tookes (2013)	1990–2009	CRSP	MA, MM	None	183
Thirumalai and Sinha (2011)	2002–2005	CRSP	MM, COMEAN, MM	t-Stat, Patell Z, Wilcoxon, BS t-Stat	223
Lilienfeld-Toal and Ruenzi (2014)	1988–2010	CRSP	MA, MM	t-Stat	not reported
Vyas (2011)	2007–2008	CRSP	BH_IND	None	406
Wang and Welker (2011)	2002–2009	Datastream	MM, BH_IND	None	1,431
Wang (2014)	2001–2008	Datastream	FM	None	34,357
Williams (2013)	1985–2011	CRSP	BH_MATCH	None	202,326
Zhao (2017)	1994–2009	CRSP	unknown	None	>480,000

Benchmark models are raw returns (RAW), the constant mean return model (COMEAN) (MacKinlay 1997, p. 17), the market-adjusted return model (MA), returns adjusted against a benchmark which is not the market index (BA), the market model (MM) (MacKinlay 1997, p. 18), a multiple-factor model (FM) (e.g., Peress 2010, Fn. 27), buy-and-hold abnormal returns against a single market index (BH_IND) (e.g., Ashbaugh-Skaife et al. 2009, p. 32), buy-and-hold abnormal returns against an individual benchmark (BH_MATCH), e.g., matched portfolio returns (e.g., Lyon et al. 1999, p. 167–173), the calendar portfolio approach (CAL) (e.g., Lyon et al. 1999, p. 192–197), the event parameter approach (EP), the capital asset pricing model (CAPM) (MacKinlay 1997, p. 19), the returns across time and securities model (IRATS) (Ibbotson 1975), the post-event alpha estimation (PEA) (e.g., Anderson et al. 2012, p. 375), beta-adjusted buy-and-hold abnormal returns (Dellavigna and Pollet 2009, p. 721), and "unknown", which means that the author(s) do(es) not report which benchmark model they use. Test statistics are simple cross-sectional or time-series t-tests of whether abnormal returns are different from zero (t-Stat), the crude dependence adjustment (CDA) (Brown and Warner 1980, pp. 223, 253), the (Patell 1976, p. 254–258) test (Patell Z), the Boehmer et al. (1991, pp. 258–270) test of standardized residuals corrected for event-induced changes in volatility (BMP), the Kolari and Pynnonen (2010, p. 4003) test of standardized residuals corrected for event-induced changes in volatility and cross-correlation (KP), the Corrado (1989, pp. 387–388) rank test or the Corrado and Zivney (1992, pp. 345-346) rank test corrected for event-induced volatility of rankings (Corrado), the generalized sign test according to Cowan (1992, pp. 345–346), the Wilcoxon (1945) signed-ranks test, and bootstrapped versions of the t-test (e.g., Lyon et al. 1999, pp. 173–175).

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