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What should be the dependent variable in marketing-related event studies?

Bernd Skiera [*,1], Emanuel Bayer [1], Lisa Schöler

Department of Marketing, Faculty of Business and Economics, Goethe University Frankfurt, Theodor-W.-Adorno-Platz 4, 60323 Frankfurt, Germany

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ABSTRACT

Most event studies rely on cumulative abnormal returns, measured as percentage changes in stock prices, as their dependent variable. Stock price reflects the value of the operating business plus non-operating assets minus debt. Yet, many events, in particular in marketing, only influence the value of the operating business, but not non-operating assets and debt. For these cases, the authors argue that the cumulative abnormal return on the operating business, defined as the ratio between the cumulative abnormal return on stock price and the firm-specific leverage effect, is a more appropriate dependent variable. Ignoring the differences in firm-specific leverage effects inflates the impact of observations pertaining to firms with large debt and deflates those pertaining to firms with large non-operating assets. Observations of firms with high debt receive several times the weight attributed to firms with low debt. A simulation study and the reanalysis of three previously published marketing event studies shows that ignoring the firm-specific leverage effects influences an event study's results in unpredictable ways.

1. Introduction

Event studies, originally pioneered in accounting and finance (for a review, see Corrado, 2011), are a popular method for assessing the valuation that financial markets attribute to marketing-related events (Johnston, 2007; Sorescu, Warren, & Ertekin, 2017). This method is based on the idea that the stock price reflects the true value of a firm (i.e., all discounted future cash flows) because it incorporates all relevant information. Accordingly, assuming that financial markets are efficient, i.e., that the financial value of new information is rapidly assimilated into stock prices, the value of an unanticipated event can be determined on the basis of subsequent stock price changes (Fama, 1970, 1991).

An event study entails collecting a sample of observations of one event type and then, in most cases, carrying out the following two steps: First, for each observation, the method estimates the cumulative abnormal percentage change in the stock price over a given time period around the event. We call this change the *cumulative abnormal percentage return on shareholder value* (CAR^{SHV}). We use the term "shareholder value" to refer to a firm's market capitalization, which is equal to the share price multiplied by the number of shares outstanding. Second, to identify determinants of this change, a regression is carried out in which CAR^{SHV} is the dependent variable and characteristics of the firm or the event serve as independent variables.

* Corresponding author.
E-mail addresses: skiera@skiera.de (B. Skiera), embayer@wiwi.uni-frankfurt.de (E. Bayer), lschoeler@wiwi.uni-frankfurt.de (L. Schöler).
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Most marketing event studies analyze the financial value of marketing-related events, such as (cobranded) new product (pre)announcements (e.g., Bornemann, Schöler, & Homburg, 2015; Cao & Sorescu, 2013), brand value announcements (Dutordoir, Verbeeten, & De Beijer, 2015), innovation-related announcements (e.g., Borah & Tellis, 2014; Sood & Tellis, 2009), CMO successions (Wang, Saboo, & Grewal, 2015), product recalls (Hsu & Lawrence, 2016), company name changes (Horsky & Swyngedouw, 1987), announcements of alliances (Mani & Luo, 2015; Swaminathan & Moorman, 2009), decisions to outsource customer support (Raassens, Wuyts, & Geyskens, 2014), or customer satisfaction announcements (Ivanov, Joseph, & Wintoki, 2013). These events influence the value of a firm's operating assets, which constitute the operating business (Damodaran, 2006). In particular, we know that marketing events impact a firm's intangible assets, a specific type of operating assets (for review see Srinivasan & Hanssens, 2009). Changes in the value of the operating business then impact shareholder value.

However, a firm's value to its shareholders depends upon its operating business as well as its financial structure, i.e., its quantities of non-operating assets and debt, which can be substantial (Schulze, Skiera, & Wiesel, 2012). Some firms have high quantities of non-operating assets such as cash and marketable securities — e.g., Apple and Microsoft had cash reserves of about $216 and $103 billion at the end of 2015 — and these assets have a positive influence on shareholder value (Damodaran, 2006). Other firms issue corporate bonds and have significant bank debt, which negatively influences shareholder value.

We suggest that, in attempting to assess the value of a marketing-related event, it is necessary to carefully examine whether the event is expected to influence (i) all value components of a firm's value, which are the value a firm's operating business, its non-operating assets and its debt, or (ii) only the operating business. Specifically, we propose that if the event only influences the value of the operating business, then the CAR^{SHV} variable, which captures all aspects of a firm's value, may not be the appropriate dependent variable. In this case, we recommend the use of the *cumulative abnormal percentage return on the value of the operating business* (CAR^{OB}) instead of CAR^{SHV}. CAR^{OB} can easily be calculated as the ratio between CAR^{SHV} and the firm-specific leverage effect. The latter relates the value of a firm's operating business (i.e., shareholder value minus non-operating assets plus debt) to its shareholder value and is a metric to capture the financial structure of the firm (Schulze et al., 2012).

Literature and practitioners suggest that most marketing-related events only influence the value of the operating business, but not non-operating assets and debt. In particular, our interdisciplinary literature review reveals just three marketing-related events where an impact on non-operating assets and debt could be possible. Our in-depth interviews with a senior analyst and an investment fund manager, suggest that in practice even the rather drastic marketing events revealed by the literature review would only lead to a re-evaluation of the value of the firm's operating business. Nevertheless, we argue that the more likely an event impacts the firm's risk structure or financial needs above and beyond its working capital, the more researchers should consider an impact of the event on non-operating assets and debt as well. The reason is that for these kinds of events, at least theoretically, we cannot exclude an impact on debt (e.g., through impact on firm's credit rating) or non-operating assets (e.g., alternative use of excess cash with different return) ex ante.

We show that results obtained in cross-sectional studies using CAR^{OB} instead of CAR^{SHV} are likely to differ because heterogeneity in the firms' financial structures inflates the impact of observations pertaining to firms with large debt and deflates those pertaining to firms with large non-operating assets. Such biases can influence a study's conclusions regarding the size of the impact of a marketing-related event and, even worse, can provide misleading evidence regarding the sign of the impact: value-creating events can easily be classified as value-destroying events and vice versa.

Thus, the aim of this paper is to encourage researchers to consider their choices of dependent variables carefully and to use CAR^{OB} where appropriate, instead of CAR^{SHV}, or to report results for both dependent variables and then argue which one is most suitable for the problem at hand. Stated differently, we feel that the choice of the dependent variable in marketing-related event studies warrants much more discussion than it currently receives.

In the following, we briefly describe the event study methodology, and provide an overview of how previous research has considered the financial structure in marketing-related event studies. Then, we show in our conceptual framework how the event type should affect the choice of the dependent variable, and how to derive CAR^{OB} from the firm-specific leverage effect and from CAR^{SHV}. Next, we provide a numerical example to illustrate why models using CAR^{SHV} as the dependent variable yield different results than models using CAR^{OB} as the dependent variable. In a subsequent simulation study, we further explore the deviations between CAR^{OB} and CAR^{SHV} and analyze the conditions under which they are particularly strongly dispersed. Finally, we reanalyze three previously published marketing event studies and compare the published results with the results that emerge when choosing CAR^{OB} instead of CAR^{SHV} as a dependent variable. We end with a summary and conclusion.

2. Current practice in event studies

2.1. Description of event study methodology

An event study usually consists of two steps (for a detailed description of the event study methodology, see for example McWilliams & Siegel, 1997, Sorescu et al., 2017). For the purpose of simplicity, we describe them as consecutive steps, although they might be carried out simultaneously.

In the first step, the event study calculates the percentage change in the stock price of each firm-instance observation[2] due to the arrival of new information (i.e., the event). The standard approach calculates the percentage change in a firm's share price, and

[2] Note that event studies usually use multiple observations per firm, i.e., a firm features several events of the same type at different time points. Therefore, we use the term firm-instance observation to unambiguously identify each observation in the sample.

then the abnormal returns. The percentage abnormal return on a firm's shareholder value equals the percentage change in a firm's share price minus the expected rate of return on the share price, frequently measured by using Fama and French's factors. Significant differences between a firm's actual rate of return and the expected rate of return reflect abnormal returns caused by the event. The cumulative abnormal return on shareholder value (CAR^{SHV}) represents the sum of abnormal returns over the event window.

At the end of the first step, it is customary to calculate the average cumulative abnormal return across all firm-instances in the sample in order to determine whether the value of the event is, on average, positive or negative. In the second step, the event study uses the cumulative abnormal return on shareholder value (CAR^{SHV}) as a dependent variable and regresses it on a number of characteristics that might explain the variability in the values of the firm-instance observations.

2.2. Dependent variables in previous event studies

The large majority of event studies conducted in finance and accounting and all event studies conducted in marketing use CAR^{SHV} as their dependent variable. Thus, these event studies (implicitly) assume that an event impacts all value components of the firm (i.e., operating business; non-operating assets and debt).

Much fewer event studies in finance and accounting used the cumulative abnormal returns on bond prices as their dependent variable (Goh & Ederington, 1993; Hand, Holthausen, & Leftwich, 1992). These studies examine the effect of an event (e.g., a bond rating agency announcement) on the prices of corporate bonds. Hence, these studies explicitly focus on the debt component in shareholder value. A common challenge of these studies is that not all firms issue corporate bonds, and if a firm does so, its corporate bonds just represent one part of the firm's total debt. So far, no prior work in accounting, finance, or marketing differentiated between events that impact all value components of the firm and events that only impact the value of the firm's operating business.

2.3. Treatment of firm's financial structure in marketing-related event studies

Most marketing-related event studies ignore the differences in the financial structure across firms (for reviews, see Johnston, 2007; Kimbrough & McAlister, 2009; Srinivasan & Hanssens, 2009, Sorescu et al., 2017). We have found only two event studies in marketing in which the authors included the financial structure as a control variable in the second step of their event study: Gielens, Van de Gucht, Steenkamp, and Dekimpe (2008) find that firms with high debt achieve lower CAR^{SHV} than do firms with low debt. Chaney, Devinney, and Winer (1991) outline that their sample's leverage is slightly below the average.

3. Conceptual framework: considering the leverage effect in event studies

We proceed by developing a framework that outlines why CAR^{OB} should be the dependent variable for events that only impact the value of the operating business. We first elaborate on how valuation theory considers operating assets, non-operating assets, and debt to derive a firm's total value of equity. Next, we illustrate how the event type should affect the choice of the dependent variable, which can be either CAR^{SHV} or CAR^{OB}. We then elaborate on the leverage effect, introduced briefly above, and describe how it links the value of the operating business to shareholder value. We finally show how to derive CAR^{OB} from CAR^{SHV}.

3.1. Operating assets, non-operating assets, and debt

To understand why some events may influence all value components of the firm, whereas others influence only the value of the operating business, it is important to understand the difference between operating assets and non-operating assets, and how valuation theory considers these two kinds of assets as well as debt to derive a firm's total value of equity. We draw on literature from finance and accounting to derive these insights.

Operating assets are all those assets used by firms in their core business operations. Typical examples are property, plant, and equipment, natural resources, and intangible assets. Non-operating assets, also called redundant assets, usually generate some form of return, but do not play a role in a firm's operations. Typical examples are excess cash[3] and marketable securities such as commercial papers and money market instruments (Damodaran, 2006).

Deriving a firm's total value of equity entails first evaluating operating assets, non-operating assets, and debt separately from one another. Then, the value of non-operating assets is added to the value of the operating assets, and the value of debt is subtracted (Damodaran, 2006; Schulze et al., 2012). Data for non-operating assets and debt can be taken from firms' balance sheets, because they are likely to be incorporated into market capitalization (i.e., shareholder value) at close to their balance sheet levels (Holthausen & Watts, 2001, p. 21).

[3] Only the part of cash the firm does not need for its operations. Cash needed for operations is included in working capital and is not considered as an additional source of value (Damodaran, 2001).

3.2. Types of events

We differentiate between two types of events. The first type comprises events that influence all value components of the firm (i.e., operating business; non-operating assets and debt); the second type comprises events that influence the value of the operating business, but not non-operating assets and debt.

3.2.1. Events influencing all value components of the firm

Events typically explored in economics and finance, such as regulatory changes, natural disasters or mergers and acquisitions, are likely to influence both the value of the operating business and non-operating assets and debt (MacKinlay, 1997). Regulatory changes (e.g., change in tax level, introduction of a new tax) impact a firm's ability to earn money with its core business operations, and lead to a re-evaluation of non-operating assets and debt (see e.g., Elton, Gruber, Agrawal, & Mann, 2001). Natural or man-made disasters (e.g., nuclear accident, earthquake) can damage a firm's property and equipment and, at the same time, cause the prices of commercial papers to fall (e.g., Elton et al., 2001).

Our interdisciplinary literature review reveals just three marketing-related events for which theory suggests that an impact on non-operating assets and debt is possible. First, the number of pre-orderings considerably exceeding the firm's production plans can impact the relative importance of a firm's business segments and can require rising short-term debt to finance the production increase (Hall, Hutchinson, & Michaelas, 2004). Second, firing of the CMO can lead to an increase in debt as the manager's tenure has been shown to be negatively associated with the firm's overall debt (Berger, Ofek, & Yermack, 1997). Third, the firm's decision to focus on the production of unique products in the future could make it increasingly difficult for a firm to "borrow because the specific use of capital reduces the probability of an alternative use in the event of bankruptcy" (Bhaduri, 2002).

In addition to this literature review, we conducted in-depth interviews with a senior analyst and an investment fund manager, both working for two large European banks, and asked them how they considered the impact of marketing-related events on the firm's value. These experts stated that almost all events only lead to a re-evaluation of the operating business, but not of non-operating assets and debt. More precisely, the senior analyst stated:

> "In fact, we only consider the effect of an event on the operating business by adjusting the respective assumptions made in the valuation model. We take the non-operating assets and debt from the firm's balance sheet and do not make any adjustments to them following the event. Mergers and acquisitions are exceptions because the firm is likely to conduct a financial restructuring after the transaction that we have to consider."

Similarly, the investment fund manager said:

> "The effect of an event depends on the kind of event. We differentiate between two kinds of events. For example, if it is a new product announcement, then we will only consider the event's effect on the operating business through the top line. The other kind of event is an acquisition. Here we also consider the event's effect on the non-operating business and debt."

These statements suggest that in practice even rather drastic marketing events like the number of pre-orderings considerably exceeding the firm's production plans, the firing of the CMO, or the firm's decision to focus on the production of unique products in the future, only lead to a re-evaluation of the value of the firm's operating business. Nevertheless, we argue that the more likely an event impacts the firm's risk structure or financial needs above and beyond its working capital, the more researchers should consider an impact of the event on non-operating assets and debt as well. The reason is that for these kinds of events, at least theoretically, we cannot exclude an impact on debt (e.g., through impact on firm's credit rating) or non-operating assets (e.g., alternative use of excess cash with different return) ex ante. An example might be the announcement of a new project like the foundation of a research center abroad that has the purpose to develop several new products in new business areas. These "make" type announcements with a strategic character are likely to be associated with substantial capital requirements that go beyond the firm's working capital and could impact the firm's risk structure through a shift in the importance of the firm's business segments.

3.2.2. Events influencing only the value of the operating business

For the large majority of marketing events, we do not expect an effect on non-operating assets and debt. In fact, marketing actions are in most cases exclusively targeted at the operating business and are inseparable from a firm's core operating assets. Therefore, we would not expect events like the release of ratings of product quality, company name changes, celebrity endorsements, customer satisfaction announcements or brand value announcements to influence a firm's non-operating assets and debt.

We propose that when researchers use CAR^{SHV} as their dependent variable, they need to provide theoretical support to the claim that the analyzed event influences not only a firm's operating business but also its non-operating assets and debt. If no such theoretical support exists, then researchers should use CAR^{OB} as the dependent variable. Researchers might also consider reporting results for both models, i.e. one using CAR^{OB} and another using CAR^{SHV}, and then argue which one is most suitable for the problem at hand. Taken together, we want to emphasize that researchers who conduct an event study need to much better justify their choice of the dependent variable.

3.3. Derivation of leverage effect

According to valuation theory, a firm's shareholder value (SHV) is the value of the operating business (OB) plus non-operating assets (NOA) minus debt (DEBT) (Damodaran, 2006; Schulze et al., 2012):

$$SHV = OB + NOA - DEBT \tag{1}$$

Thus, a firm having an operating business worth \$100, non-operating assets of \$10 and debt of \$45.5 will have a shareholder value of \$64.5 (=\$100 + \$10 − \$45.5). The leverage effect (LE) describes how a 1% change in operating business translates into a percentage change in shareholder value. It reflects the share of the operating business at shareholder value (Schulze et al., 2012):

$$LE = \frac{OB}{SHV} = \frac{SHV - NOA + DEBT}{SHV} \tag{2}$$

The leverage effect of the example firm described above is 1.55 (LE = 100 / 64.5). This means that a 1% increase in the value of the operating business translates into a 1.55% (1 / 0.645) increase in shareholder value. We choose this value because it is the average value of the leverage effect of >2000 companies included in Standard & Poor's (S&P) Total Market Index across ten years (Schulze et al., 2012). Thus, on average, a 1% change in operating business yields a 1.55% change in shareholder value.

Eq. (2) describes the leverage effect with three publicly available variables. The shareholder value represents market capitalization and is the product of a firm's outstanding shares and the share price. Non-operating assets and debt are available in a firm's balance sheet, disclosed in quarterly and annual reports. Firms featuring more debt than non-operating assets show leverage effects that are >1; firms featuring more non-operating assets than debt show leverage effects below 1. For a firm with the same amounts of non-operating assets and debt, the leverage effect is exactly 1 (Schulze et al., 2012).

We kindly advise the reader not to mistake the leverage effect for the leverage ratio. The leverage ratio is a variable that describes a firm's amount of debt (e.g., measured as long-term debt; long-term debt + short-term debt) relative to firm size (e.g., measured as book value of equity; market capitalization; total assets; debt + equity) (e.g., Damodaran, 2006). The leverage effect[4] was introduced by Schulze et al. (2012) into marketing and describes the effect of the value of the operating business with respect to shareholder value. Its size depends on the amount of debt and non-operating assets a firm owns.

3.4. Derivation of cumulative abnormal returns on value of operating business

Formally, the cumulative abnormal return on shareholder value (CAR^{SHV}) can be expressed as:

$$CAR_i^{SHV} = R_i^{SHV} - E\left(R_i^{SHV}\right) = \frac{SHV_{i_{after}} - SHV_{i_{before}}}{SHV_{i_{before}}} - E\left(R_i^{SHV}\right) \tag{3}$$

where
CAR_i^{SHV} = cumulative abnormal return on shareholder value of the firm with firm-instance observation i,
$SHV_{i_{after}}$ = post-event shareholder value of the firm with firm-instance observation i,
$SHV_{i_{before}}$ = pre-event shareholder value of the firm with firm-instance observation i, and
$E(R_i^{SHV})$ = expected rate of return on the share price of the firm with firm-instance observation i.[5]

The difference in shareholder value ($SHV_{i_{after}} - SHV_{i_{before}}$) adjusted for the expected rate of return is what is sometimes also called the net present value of the event (Rao, Chandy, & Prabhu, 2008; Sorescu, Chandy, & Prabhu, 2003). Analogously, we can express CAR^{OB} as:

$$CAR_i^{OB} = R_i^{OB} - E\left(R_i^{OB}\right) = \frac{OB_{i_{after}} - OB_{i_{before}}}{OB_{i_{before}}} - E\left(R_i^{OB}\right) \tag{4}$$

[4] Please note that in finance and accounting the term leverage effect describes the generally negative correlation between an asset return and its volatility, which is a characteristic of many equity markets (e.g., Ait-Sahalia, Fan, & Li, 2013; Cheung & Ng, 1992). Furthermore, the term leverage effect is frequently used to describe that firms can increase their return on equity by investing borrowed money (instead of equity) into the operating business if the return on the borrowed money is higher than its cost (e.g., Damodaran, 2006).

[5] Different approaches are used such as the market model, Capital Asset Pricing Model or the Fama-French-three-factor model to determine the expected rate of return on shareholder value ($E(R^{SHV})$).

where
CAR_i^{OB} = cumulative abnormal return on the value of the operating business of the firm with firm-instance observation i,
$OB_{i_{after}}$ = post-event value of the operating business of the firm with firm-instance observation i,
$OB_{i_{before}}$ = pre-event value of the operating business of the firm with firm-instance observation i, and
$E(R_i^{OB})$ = expected rate of return on the value of the operating business of the firm with firm-instance observation i.

We now derive the relation between CAR^{OB} and CAR^{SHV}. We start by considering the first part on the right-hand side of Eq. (4), the rate of return, R_i^{OB}, and solve Eq. (1) for OB, which we then insert into Eq. (5):

$$R_i^{OB} = \frac{OB_{i_{after}} - OB_{i_{before}}}{OB_{i_{before}}} = \frac{SHV_{i_{after}} - SHV_{i_{before}}}{SHV_{i_{before}} - NOA_i + DEBT_i} \tag{5}$$

Multiplying Eq. (5) by $\frac{\frac{1}{SHV_{i_{before}}}}{\frac{1}{SHV_{i_{before}}}}$ enables us to rewrite Eq. (5) as:

$$R_i^{OB} = \frac{\left(SHV_{i_{after}} - SHV_{i_{before}}\right) \cdot \frac{1}{SHV_{i_{before}}}}{\left(SHV_{i_{before}} - NOA_i + DEBT_i\right) \cdot \frac{1}{SHV_{i_{before}}}} = \frac{\frac{SHV_{i_{after}} - SHV_{i_{before}}}{SHV_{i_{before}}}}{\frac{(DEBT_i - NOA_i)}{SHV_{i_{before}}} + 1} = \frac{R_i^{SHV}}{LE_{i_{before}}} \tag{6}$$

Analogously, we determine the expected rate of return on the value of the operating business $E(R_i^{OB})$ as:

$$E\left(R_i^{OB}\right) = \frac{E\left(R_i^{SHV}\right)}{LE_{i_{before}}} \tag{7}$$

Finally, substituting Eqs. (7) and (6) in Eq. (4) yields:

$$CAR_i^{OB} = \frac{R_i^{SHV}}{LE_{i_{before}}} - \frac{E\left(R_i^{SHV}\right)}{LE_{i_{before}}} = \frac{CAR_i^{SHV}}{LE_{i_{before}}}. \tag{8}$$

Eq. (8) shows that the leverage effect links the two abnormal return measures. For each firm-instance observation, CAR^{SHV} equals CAR^{OB} if the leverage effect is 1 (i.e., when non-operating assets equal debt). If the leverage effect is larger than 1, CAR^{SHV} will be larger than CAR^{OB} if CAR^{OB} is positive, and smaller than CAR^{OB} if CAR^{OB} is negative. Conversely, if the leverage effect is smaller than 1, CAR^{SHV} will be smaller than CAR^{OB} if CAR^{OB} is positive, and larger than CAR^{OB} if CAR^{OB} is negative. Table 1 summarizes the relationship between CAR^{SHV} and CAR^{OB} for different values of the leverage effect and signs of CAR^{OB}.

Thus, large differences between CAR^{SHV} and CAR^{OB} occur for firms with leverage effects whose values are far away from 1. This finding implies that taking the mean of CAR^{SHV} across firm-instance observations is problematic if the firm-instance observations pertain to firms with different financial structures represented by different leverage effects. The reason is that the leverage effect inflates or deflates the "true" effect of an event, which is captured by CAR^{OB}.

Table 1
Relationships between cumulative abnormal returns on shareholder value (CAR^{SHV}) and operating business (CAR^{OB}).

	LE = 1	LE > 1	LE < 1
$CAR^{OB} > 0$ (Positive effect)	$CAR^{SHV} = CAR^{OB}$ (Correct estimation)	$CAR^{SHV} > CAR^{OB}$ (Inflation of "true" effect)	$CAR^{SHV} < CAR^{OB}$ (Deflation of "true" effect)
$CAR^{OB} < 0$ (Negative effect)	$CAR^{SHV} = CAR^{OB}$ (Correct estimation)	$CAR^{SHV} < CAR^{OB}$ $\lvert CAR^{SHV}\rvert > \lvert CAR^{OB}\rvert$ (Inflation of "true" effect)	$CAR^{SHV} > CAR^{OB}$ $\lvert CAR^{SHV}\rvert < \lvert CAR^{OB}\rvert$ (Deflation of "true" effect)

LE: Leverage effect, CAR^{SHV}: cumulative abnormal return on shareholder value; CAR^{OB}: cumulative abnormal return on operating business; |x| represents the absolute value of x.

Table 2
Setup and results for the numerical example.

Calculations			Shop A	Shop B	Shop C
Base case	I	Value of operating business	$1000	$1000	$1000
	II	Non-operating assets	$0	$1000	$0
	III	Debt	$0	$0	$900
	IV = I + II − III	Shareholder value (before events)	$1000	$2000	$100
	V = I / IV	Leverage effect	1.0	0.5	10.0
9 observations (average leverage effect = 3.83)					
Event	VI	Value of Event 1 (Event 2; Event 3)	$30 (− $60; $50)	$30 (− $60; $50)	$30 (− $60; $50)
	VII	Mean value (per event)		Event 1: $30 (Event 2: − $60; Event 3: $50)	
	VIII	Mean value (overall)		$6.66	
	IX = IV + VI	Shareholder value (after events)	$1030 ($940; $1050)	$2030 ($1,940; $2050)	$130 ($40; $150)
CAR^{SHV}	X = VI / IV	CAR^{SHV} (per shop & event)	3% (− 6%; 5%)	1.5% (− 3%; 2.5%)	30% (− 60%; 50%)
	XI	Mean CAR^{SHV} (per event)		Event 1: 11.50% (Event 2: − 23.00%; Event 3: 19.17%)	
	XII	Mean CAR^{SHV} (overall)		2.56%	
CAR^{OB}	XIII = VI / I	CAR^{OB} (per shop & event)	3% (− 6%; 5%)	3% (− 6%; 5%)	3% (− 6%; 5%)
	XIV	Mean CAR^{OB} (per event)		Event 1: 3.00% (Event 2: − 6.00%; Event 3: 5.00%)	
	XV	Mean CAR^{OB} (overall)		0.67%	
	XVI	Correlation between CAR^{OB} and leverage effect		0.00	
8 observations (average leverage effect = 3.06)					
Event	XVII	Value (per shop & event)	$30 (− $60; 50)	$30 (− $60; $50)	$30 (− $60)
	XVIII	Mean value (per event)		Event 1: $30 (Event 2: − $60; Event 3: $50)	
	XIX	Mean value (overall)		$1.25	
	XX = IV + XVII	Shareholder value (after events)	$1030 ($940; $1050)	$2030 ($1940; $2050)	$130 ($40)
CAR^{SHV}	XXI = XVII / IV	CAR^{SHV} (per shop & event)	3% (− 6%; 5%)	1.5% (− 3%; 2.5%)	30% (− 60%)
	XXII	Mean CAR^{SHV} (per event)		Event 1: 11.50% (Event 2: − 23.00%; Event 3: 3.75%)	
	XXIII	Mean CAR^{SHV} (overall)		− 3.38%	
CAR^{OB}	XXIV = XVII / I	CAR^{OB} (per shop & event)	3% (− 6%; 5%)	3% (− 6%; 5%)	3% (− 6%)
	XXV	Mean CAR^{OB} (per event)		Event 1: 3.00% (Event 2: − 6.00%; Event 3: 5.00%)	
	XXVI	Mean CAR^{OB} (overall)		0.13%	
	XXVII	Correlation between CAR^{OB} and leverage effect		− 0.19	

CAR: cumulative abnormal returns; OB: operating business; SHV: shareholder value (here represents market capitalization).

4. Illustration of conceptual framework

4.1. Numerical example

We use the following simplified example to illustrate our conceptual framework: Three firms A, B, and C represent three ice cream shops with identical characteristics and an operating business that is worth $1000 (i.e., the discounted value of the ice cream cash flows is $1000). We also assume that each ice cream shop owns $1000 in excess cash which is not needed to run the ongoing operations. Thus, each ice cream shop has a value of $1000 + $1000 = $2000.

Now, each ice cream shop is sold for its value of $2000. The buyer of the first ice cream shop took $1000 out of his private money and the $1000 that the shop had as excess cash to pay the seller. Thus, after the transaction, the value of this first shop is $1000 because the excess cash is gone. The buyer of the second ice cream shop takes $2000 of his private money to pay the seller. Thus, after the transaction, the value of this second shop is still $2000. The buyer of the third ice cream shop takes $100 of his private money, the $1000 that the shop had as excess cash, and a loan of $900 from the bank on behalf of the ice cream shop to pay the seller. Let the interest rate of the loan be equivalent to the discount rate so that the net present value of the loan equals $900. Thus, after the transaction, the value of this third shop is $100.

Three events occur. The first event ("celebrity endorsement") is that a local celebrity becomes a frequent customer of the ice cream shops, thus attracting new customers. Let the net present value of the increase in profits (for simplification purposes, we assume that profits equal cash flows) of each ice cream shop be $30. The second event ("rating of product quality") is that the local newspaper publishes an article revealing that the ice cream sold in the three shops is of low quality. Let the net present value of the change in profits of each ice cream shop be −$60. The third event ("company name change") is the renaming of each shop with a more distinctive company name and let the net present value of the increase in profits be $50. These three events influence the values of the three shops' operating businesses equally, but they do not impact the non-operating assets (here excess cash not required to run the business) and debt of any of the three shops.

Table 2 summarizes the setup and the results of this numerical example that mimics an event study. Consistent with the language used in real event studies, we call the ice cream shop's values "shareholder values". The three shops (A, B, and C) have the same value of the operating business, $1000 (row I). They differ only with respect to their financial structures (i.e., non-operating assets and debt, see rows II and III). Thus, the shareholder values are $1000 for shop A; $2000 for shop B; and $100 for shop C (see row IV). The leverage effect is the ratio between the value of the operating business and the shareholder value (Schulze et al., 2012). Accordingly, the leverage effect of shop A is 1.0 ($1000/$1000), that of shop B is 0.5 ($1000/$2000), and that of shop C is 10.0 ($1000/$100) (see row V).

The events change the value of each firm's operating business by $30 (event 1), −$60 (event 2), and $50 (event 3) (see row VI).[6] These "true" values are the net present values of the events (Rao et al., 2008; Sorescu et al., 2003) and are, on average, positive (1/3 × ($30–$60 + $50) = $6.67). Thus, we have nine (3 × 3) observations, and the correlation between the values of the events (CAR^{OB}) and the leverage effect is 0 (i.e., the correlation between the values in row XIII and those in row V; the result is displayed in row XVI). After event 1 (event 2; event 3), the shareholder value of shop A is $1030 ($940; $1050), that of shop B is $2030 ($1940; $2050), and that of shop C is $130 ($40; $150) (see row IX, which is the sum of rows IV and VI).

CAR^{OB} is 3% for the first event, −6% for the second event, and 5% for the third event (see row XIII). The returns associated with each event are the same across all three shops, correctly reflecting that the three shops were affected equally. The average CAR^{OB} is 0.67% (see row XV). In contrast, CAR^{SHV} differs across events and shops (see row X, which is derived by comparing rows IV and IX), suggesting that the events affected the shops differently. Differences in the firms' leverage effects cause these deviations. For shop A (B; C) the CAR^{SHV} is 3% (1.5%; 30%) for event 1, −6% (−3%; −60%) for event 2, and 5% (2.5%; 50%) for event 3 (row X).

In absolute terms, the value of CAR^{SHV} is highest for shop C (row X), because that shop's debt leverages the cumulative abnormal returns on the value of the operating business (CAR^{OB}) by a factor of 10 (row V). The value of CAR^{SHV} is lowest for shop B, whose non-operating assets leverage the CAR^{OB} by a factor of 0.5. The average CAR^{SHV} across the three shops is 11.50% for the first event, −23.00% for the second, and 19.17% for the third event (row XI) and the average CAR^{SHV} across firms and events is 2.56%. This value is 3.83 times higher than the corresponding CAR^{OB} (0.67%) (compare rows XII and XV). This increase is equal to the value of the leverage effect. A comparison between CAR^{OB} and CAR^{SHV} (rows XIII and X) shows that if a shop's leverage effect is smaller than 1, the absolute value of CAR^{SHV} is smaller than the absolute value of CAR^{OB} (and vice versa for a leverage effect > 1).

4.2. Impact of leverage effect on average percentage value of event

In the preceding example we considered a situation in which the correlation between the value of each event and the leverage effect was 0. We will now examine what happens if the correlation between the leverage effect and the event value is no longer 0. This examination is important, because a situation where the leverage effect is correlated with the dependent variable can lead to stronger differences between models using CAR^{SHV} and models using CAR^{OB}.

We therefore drop one observation, specifically, the ninth observation, so that shop C is not subject to the third event, which features a value of $50. Thus, we now consider just 8 observations. The average "true" value of event 3 is still positive ($1.25). Yet, the correlation between the values of all the events (or CAR^{OB}) and the leverage effect is now negative (compare −0.19 in row XXVII with 0.00 in row XVI).

Whereas the average CAR^{OB} of the third event remains unaffected (compare rows XIV and XXV), the average CAR^{SHV} of the third event decreases from 19.17% to 3.75% (compare rows XI and XXII). The two shops that are subject to the third event are characterized by relatively low leverage effects, so that the absolute size of the event has a moderate effect on the percentage change in shareholder value. Not surprisingly, the average CAR^{OB} across firms and events for 8 observations (0.13%) is smaller than for 9 observations (0.67%), but its sign remains the same (compare rows XXVI and XV) and is still in line with the average positive value of the events.

In contrast, the average CAR^{SHV} changes sign. It is now negative (−3.38%) (row XXIII) and no longer reflects the average positive value of the events. Hence, differences in shops' leverage effects may lead to a situation in which the average value of CAR^{SHV} differs from the average "true" value of the event not only in size but also in sign.

4.3. Explaining differences in event values

The second step of an event study usually uses CAR^{SHV} as the dependent variable and regresses it on characteristics of the event to identify determinants of the value of the event. We do so for 8 and for 9 observations. In Model I, we calculate a traditional model in which the dependent variable is CAR^{SHV} and the independent variables are two dummy variables corresponding, respectively, to events 2 (value of $−60) and 3 (value of $50). Thus, the two dummy variables represent the characteristics that are used to explain CAR^{SHV}. In Model II, we include the leverage effect as an additional independent variable. In Model III, we use CAR^{OB} as the dependent variable and the two dummy variables of events 2 and 3 as independent variables. Table 3 summarizes the results.

When we compare the results for 8 and for 9 observations, several remarkable findings emerge. First, the results for the two regressions differ for the dependent variable CAR^{SHV} (Models I and II). The coefficient of the dummy variable of event 3 is positive in the case of 9 observations and negative in the case of 8 observations. Yet, given the "true" values of the events, the coefficient of event 3 should be positive (i.e., larger than that of event 1, which is zero here). Thus, the use of CAR^{SHV} as a dependent variable can yield coefficients whose signs do not match the signs of the "true" values of the corresponding events. Notably, controlling linearly for the leverage effect (Model II) does not prevent this result from occurring. The reason is that the leverage effect moderates each independent variable and thus cannot simply be included as a control variable in the regression.

The only way to avoid obtaining these misleading findings is to use CAR^{OB} as the dependent variable (Model III), which is easy to accomplish as CAR^{OB} is the ratio between CAR^{SHV} and the leverage effect. The sizes and signs of the coefficients obtained using

[6] We select rather large values for the events for the ease of exposition. Additionally, we assume that the expected return of the stock is zero. This assumption just implies that the return of a corresponding benchmark—for example, the average return of other publicly listed firms in the same industry—is zero. This assumption could easily be relaxed at the expense of making the exposition more difficult.

Table 3
Regression results for the numerical example.

	Model I: CAR^{SHV}		Model II: CAR^{SHV}		Model III: CAR^{OB}	
	9 observations	8 observations	9 observations	8 observations	9 observations	8 observations
$Dummy_{Event2}$	−0.3450	−0.3450	−0.3450	−0.3450	−0.09	−0.09
$Dummy_{Event3}$	0.0767	−0.0775	0.0767	−0.1235	0.02	0.02
Leverage			0.0067	0.0149		
Intercept	0.1150	0.1150	0.0894	0.1722	0.03	0.03
N	9	8	9	8	9	8
R^2	0.43	0.43	0.44	0.48	1.00	1.00
Adj. R^2	0.24	0.20	0.11	0.10	1.00	1.00

CAR^{OB} reflect those of the "true" values of the events. Technically, Model III is equivalent to a model in which CAR^{SHV} is the dependent variable and the independent variables are the interactions of the leverage effect with all of the previous independent variables. We prefer to change the dependent variable instead of all independent variables because the dependent variable "operating business" more appropriately describes what the marketing-related event is supposed to impact. Additionally, models with interactions usually consider direct effects of independent variables and selectively add a few interactions to make more nuanced statements rather than only considering the impact of interactions with no direct effects.

4.4. Relationship between CAR^{OB} and the efficient market hypothesis

It is important to note that models using CAR^{OB} rely on the efficient market hypothesis just like models using CAR^{SHV}. That is, both types of models (i.e., those using CAR^{OB} and those using CAR^{SHV}) assume that markets are efficient and that investors consider differences in firms' financial structures. Hence, in the numerical example, the financial market is right in assigning different CAR^{SHV} values (i.e., percentage values) to the three firms for an event that impacts the shops' operating businesses equally, but does not impact non-operating assets and debt. Only the differences in the shops' financial structures translate the event's same (absolute and relative) effect on the values of the shops' operating businesses into different (relative) CAR^{SHV} values.

In case of a marketing-related event that influences the value of the operating business, but not non-operating assets and debt, looking at these different CAR^{SHV} values will likely result in the misleading conclusion that the event affected the shops differently. This conclusion, however, is not true because the differences in CAR^{SHV} occur because of the differences in the shops' financial structures. The empirical study in Appendix A outlines that differences across firms' financial structures are fairly large.

Therefore, for events that only influence the value of the operating business, CAR^{OB} should be used as the dependent variable. As we elaborated in Section 3.4, the derivation of CAR^{OB} relies on valuation theory which suggests that a firm's shareholder value equals the value of the operating business plus non-operating assets minus debt (e.g., Damodaran, 2006; Schulze et al., 2012). Thus, based on valuation theory we can analyze how an event impacts the value of the operating business by deducting non-operating assets from and adding debt to shareholder value.

In what follows we present a simulation study in which we further explore the deviations between CAR^{OB} and CAR^{SHV} and analyze under which conditions these deviations are particularly strongly dispersed. Then we reanalyze three previously published marketing-related event studies and compare the results that emerge when using CAR^{OB} instead of CAR^{SHV} as the dependent variable.

5. Simulation study

In the following simulation study, we further explore the differences between CAR^{OB} and CAR^{SHV} and analyze under which conditions these differences are particularly strong. In particular, we analyze the results obtained in each of the two steps of an event study. For the first step, which aims to determine the cumulative abnormal returns associated with specific events, we show how strongly CAR^{SHV} differs from CAR^{OB} and we quantify how often one can expect signs of CAR^{SHV} and CAR^{OB} to differ. Also, we analyze how often models using CAR^{SHV} fail to detect a significant cumulative abnormal return and how often they erroneously find a significant cumulative abnormal return.

For the second step, which aims to explain differences in event values across observations, we carry out analyses similar to those described for the first step, but now focus on the differences in the independent variables' coefficients of models using CAR^{SHV} and CAR^{OB}, respectively. We analyze whether the signs and significance levels of the coefficients differ between the two models and we analyze how often models using CAR^{SHV} fail to detect a significant coefficient and how often they erroneously find a significant coefficient.

5.1. Setup of simulation study

We build upon Eq. (8) and assume that the relationship between CAR^{OB} (the dependent variable) and two independent variables x1 and x2 is:

$$CAR_i^{OB} = \alpha + \beta_1 x1_i + \beta_2 x2_i. \tag{9}$$

Table 4
Setup of simulation study.

Experimental factors	Number of factor levels	Factor levels
Leverage effect	1	• Random draw from log-logistic distribution fitted on real data (scale parameter = 4.41, shape parameter = 1.22)
Coefficient α, β_1, β_2	1	• $\alpha = 0.1, \beta_1 = 0.2, \beta_2 = -0.4$
Variable x1	1	• Uniform Distribution [−10; +10]
Variable x2	1	• Uniform distribution [−10; +10]
Number of firm-instance Observations (i.e., sample size)	2	• Small: 100 • Large: 500
Number of experimental settings	2	
Number of replications	100	
Number of event studies	$100 \cdot 2 = 200$	

For each firm-instance observation, we randomly draw values for variables x1 and x2 from uniform distributions and set $\alpha = 0.1$, $\beta_1 = 0.2$ and $\beta_2 = -0.4$. We also randomly draw a value for the leverage effect from a log-logistic distribution that best fits the empirical distribution of the leverage effects of firms listed in the S&P Total Market Index (for a detailed analysis of the empirical distribution of firms' leverage effects see Appendix A). To account for differences in sample size—notably, sample sizes are usually rather small in event studies—we distinguish between a small sample with 100 firm-instance observations and a larger sample with 500 firm-instance observations. For each of these two experimental settings, we replicate the analysis 100 times, so that we generate data for 200 different event studies (i.e., 100 studies each contain 100 firm-instance observations; the other 100 studies each contain 500 firm-instance observations). Table 4 summarizes the setup of this simulation study.

5.2. Calculation of percentage deviations

We start by conducting the first step of an event study and calculate for each firm-instance observation i in an event study r the values of CAR_{ri}^{OB} (Eq. 9) and CAR_{ri}^{SHV} ($=CAR_{ri}^{OB} \times LE_{ri}$, see Eq. 8). We then calculate for every event study r the average values CAR_{ri}^{OB} and CAR_{r}^{SHV} as well as LE_r. We calculate our variable of interest, namely the ratio of CAR_r^{SHV} and CAR_r^{OB} as follows:

$$RATIO_r^{CAR} = \frac{CAR_r^{SHV}}{CAR_r^{OB}} - 1 \tag{10}$$

A value of $RATIO_r^{CAR}$ equal to 0 indicates that CAR_r^{SHV} is equal to CAR_r^{OB}.[7] Values of $RATIO_r^{CAR} \neq 0$ indicate that CAR_r^{SHV} differs from $CAR_r^{OB}$and negative values indicate that even the signs of CAR_r^{SHV} and CAR_r^{OB} differ.

Additionally, we look at how strongly the results differ for the second step of the event study. Therefore, we run two separate regressions for each event study r with CAR_{ri}^{SHV}, respectively CAR_{ri}^{OB}, as the dependent variable and $x1_{ri}$ and $x2_{ri}$ as the independent variables. Again, we calculate the percentage deviation of each event study's estimated coefficients for CAR^{SHV} (α_r^{est}, β_{r1}^{est}, β_{r2}^{est}) from the "true" values of the CAR^{OB} model ($\alpha = 0.1$, $\beta_1 = 0.2$, $\beta_2 = -0.4$):

$$RATIO_r^{Coeff} = \frac{Coeff_r^{SHV}}{Coeff_r^{OB}} - 1 \text{ with : } Coeff_r = \{\alpha_r, \beta_{1r}, \beta_{2r}\} \tag{11}$$

The interpretation of $RATIO_r^{Coeff}$ is similar to that of $RATIO_r^{CAR}$. $RATIO_r^{Coeff} = 0$ indicates that the estimated coefficient is equal to the "true" value[7]. Again, values of $RATIO_r^{Coeff} \neq 0$ indicate that the estimated coefficients differ from the true values and negative values indicate that even the signs of the coefficients differ.

5.3. Illustration of simulation study's results using the numerical example

We illustrate the interpretation of $RATIO_r^{CAR}$ and $RATIO_r^{Coeff}$ by reconsidering our numerical example from Section 4. In the case of 9 observations, the average $CAR^{SHV} = 2.56\%$ (row XII in Table 2) is much larger than the average value of $CAR^{OB} = 0.67$ (row XV in Table 2). Thus, $RATIO^{CAR} = (2.56 / 0.67) - 1 = 2.83$. This result indicates that CAR^{SHV} is larger than CAR^{OB}.

The comparison of the estimated coefficients of the regression model using CAR^{SHV} as the dependent variable (Model 1, Table 3) with the coefficients of the regression model using CAR^{OB} as the dependent variable (Model 3, Table 3) yields $RATIO^{Event2} = (-0.3450 / -0.09) - 1 = 2.83$, $RATIO^{Event3} = (0.0767 / 0.02) - 1 = 2.83$ and $RATIO^{intercept} = (0.1150 / 0.03) - 1 = 2.83$. Here, again, ignoring leverage effects increases all values.

[7] Note that RATIO = 0 could be associated with non-zero deviations for individual firm-instance observations which even out on the sample level. Our simulation study rightly captures this case because it could also occur in reality. Exclusion of this case would lead to an overestimation of the error made when choosing CAR^{SHV} instead of CAR^{OB} as the dependent variable, thus exaggerating the risk of deriving wrong substantive conclusions in real event studies.

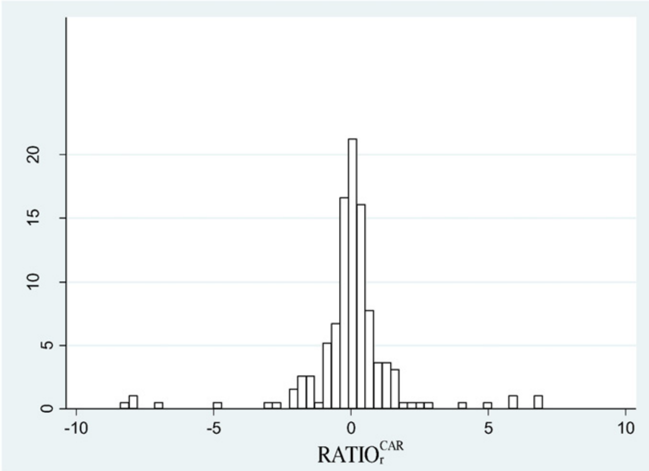

Fig. 1. Histogram of ratio ($RATIO_r^{CAR}$) between CAR^{SHV} and CAR^{OB}. Notes: Mean = 0.11, SD = 12.21, N = 200. For better readability, the histogram just includes $-10 < RATIO^{CAR} < 10$.

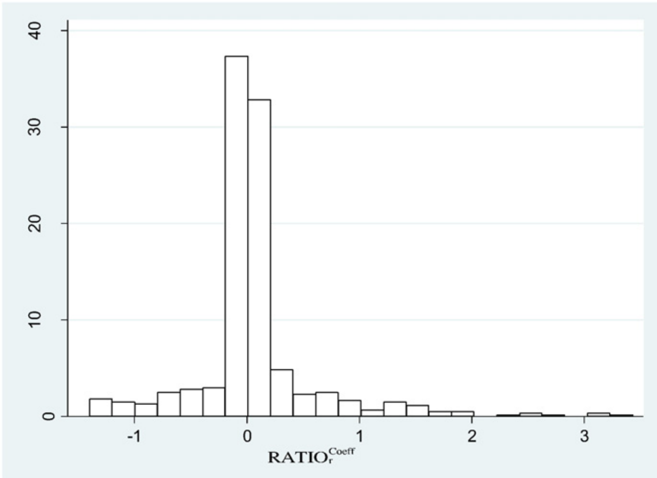

Fig. 2. Histogram of ratio ($RATIO_r^{Coeff}$) between coefficients of models with CAR^{SHV} as dependent variable and coefficients of models with CAR^{OB} as dependent variable. Notes: Mean = 0.06, SD = 0.55, N = 200 event studies × 3 coefficients = 600.

In the case of 8 observations, values differ not only in size but even in their signs. $RATIO^{CAR} = (-3.38\% / 0.13\%) - 1 = -28$ and hence, negative.[8] Also, the coefficients of the model using CAR^{SHV} as the dependent variable (Model 1, Table 3) differ from those of the model using CAR^{OB} as the dependent variable (Model 3, Table 3). In particular, $RATIO^{Event2} = (-0.3450 / -0.09) - 1 = 2.83$, $RATIO^{Event3} = (-0.0775 / 0.02) - 1 = -4.88$, and $RATIO^{intercept} = (0.1150 / 0.03) - 1 = 2.83$. Hence, $RATIO^{Event3}$ being negative indicates that the cofficient of the dummy variable for Event 3 has a different sign in the model with CAR^{SHV} as the dependent variable compared to the model with CAR^{OB} as the dependent variable.

5.4. Results of simulation study

Across all 200 event studies that we simulated, the average values are for $CAR^{SHV} = 0.133$, for $CAR^{OB} = 0.100$ and for $RATIO^{CAR} = 0.11$. The average $RATIO^{CAR}$ appears to be small, but its standard deviation is very high (12.21); it varies from −122.34 to 104.51. Furthermore, we find that the signs between CAR_r^{SHV} and CAR_r^{OB} differ in 10.5% of all event studies (i.e., $RATIO_r^{CAR} < 0$); the correlation between CAR_r^{SHV} and CAR_r^{OB} is only 0.10. These results suggest that if researchers carried out many event studies per event type, then the inflating and deflating effects of the firms' leverage effects would largely cancel out. The reality, however, is that researchers usually just carry out one event study per event type and that CAR_r^{SHV} and CAR_r^{OB} are likely to differ

8 We calculated $RATIO^{CAR}$ and $RATIO^{Coeff}$ with exact and not rounded values, e.g., $RATIO^{CAR} = (-3.375 / 0.125) - 1 = -28$.

Table 5
Conditions leading to differences between estimated coefficients and true values.

Independent variables	Coeff	SE	
Correlation between CAR^{OB} and leverage effect	0.37	(0.71)	***
Sample size	−0.32	(0.06)	***
Constant	−0.00	(0.38)	
N (200 event studies × 3 coefficients (α, β_1, β_2))		600	
R-square		0.05	

Dependent variable is $RATIO^{Coeff}$. Coeff = coefficient; SE = standard error.
*** $p < 0.001$ (two-sided).

substantially on the basis of a single event study. We explore the differences between CAR_r^{SHV} and CAR_r^{OB} in more detail in Fig. 1, which shows the distribution of $RATIO_r^{CAR}$.

We also analyzed CAR^{SHV}'s ability to detect cumulative abnormal returns that are significantly different from zero (at a 5% level). We find that in 28.6% of all event studies in which CAR^{OB} is significantly different from zero, models using CAR^{SHV} as the dependent variable fail to reflect this significance (false negative; type II error). Additionally, in 16.7% of all cases in which models using CAR^{SHV} as a dependent variable find a cumulative abnormal return significantly different from zero, CAR^{OB} is not actually significant (false positive, type I error).

Fig. 2 shows the distribution of $RATIO_r^{Coeff}$. The average $RATIO_r^{Coeff}$across event studies is 0.06 with a relatively large standard deviation of 0.55. Thus, even though estimated coefficients and true values do not differ much across event studies, they are again likely to differ substantially on the basis of a single event study. Furthermore, in 7% of all cases even the signs of the coefficients differ.

We also analyzed differences in the significance of coefficients between models using CAR^{SHV} and CAR^{OB}. In 9.0% of all cases in which coefficients are actually significant (at 5% level), models using CAR^{SHV} as the dependent variable fail to find this significance (false negative; type II error). Additionally, in 1.7% of all cases in which models using CAR^{SHV} as dependent variable find a significant effect, the corresponding models using CAR^{OB} indicate that no effect is present (false positive, type I error).

In order to analyze under which conditions the deviations of the estimated coefficients from the true values are particularly strongly dispersed, we run a linear regression with robust standard errors and use $RATIO_r^{Coeff}$ as the dependent variable and the correlation between CAR^{OB} and leverage effect as well as the sample size as the independent variables.

The results displayed in Table 5 show that a high deviation between estimated coefficients and true values occurs in cases of high correlation between CAR^{OB} and the leverage effect. This result is also in line with our numerical example, which showed large deviations in the case of 8 observations, i.e., the case in which CAR^{OB} and the leverage effect were correlated. Furthermore, our analysis reveals that this effect is stronger for small sample sizes than for large sample sizes. This result is particularly important, as event studies usually rely on rather small sample sizes.

In summary, our simulation study shows that in an event study CAR_r^{SHV} and CAR_r^{OB} as well as their associated coefficients might differ substantially from each other. Furthermore, different signs of CAR_r^{SHV} and CAR_r^{OB} occur not only in our numerical example but also in >10% of all event studies of our simulation study. Models using CAR^{SHV} as the dependent variable deviate particularly strongly from models using CAR^{OB} in cases of a high correlation between CAR^{OB} and the leverage effect and when sample sizes are small.

Our analyses have shown that event studies that use CAR^{OB} instead of CAR^{SHV} as a dependent variable can yield substantially different outcomes. We continue by comparing the results of three previously published marketing event studies that used CAR^{SHV} as their dependent variable with the results of an analysis using identical data but in which CAR^{OB} is the dependent variable. We start with the reanalysis of the event study that was conducted by Bornemann et al. (2015).[9]

6. First empirical study: reanalysis of the event study conducted by Bornemann et al. (2015)

6.1. Description of event study

In this event study, the authors examine how consumers' perceptions of the three most important product design dimensions (i.e., aesthetic, ergonomic, and symbolic value, see Creusen & Schoormans, 2005) as well as the interaction of each of these three design dimensions with functional product advantage are related to abnormal stock returns (i.e., CAR^{SHV}) following the unveiling of a new product's visual appearance. To do so, the authors analyze data from the automotive and consumer electronics industries, combining perceptual data at the consumer level with stock market data while controlling for brand familiarity, firm size and industry.

Aesthetic value is the design dimension most often discussed in literature and describes perceptions of the visual attractiveness of a product: visual attractiveness is expected to positively influence a product's acceptance in the target market (Orth & Malkewitz, 2008). Ergonomic value denotes the ability of a product to correctly communicate its utilitarian functions, and a high degree of ergonomic value is likely to constitute one of the main reasons for buying a given product (Creusen & Schoormans, 2005, p. 67). Finally, symbolic value is defined as the degree to which a product's appearance is perceived to have the potential to reflect the (desired) identity of its owner (Crilly, Moultrie, & Clarkson, 2004). The authors propose that investors

[9] We would like to take this opportunity to thank the authors of the three previously published event studies (Bornemann et al., 2015; Karpoff & Rankine, 1994; Kulkarni, Vora, & Brown, 2003) for providing us with the data sets of their event studies.

form expectations about consumers' perceptions of these three product design dimensions that translate into corresponding stock market reactions.

The authors find that ergonomic value has a positive influence on CAR^{SHV}, whereas symbolic value has a negative influence on CAR^{SHV} (we replicate their results in Model I, Table 6). Surprisingly, according to their results, aesthetic value does not have a main effect on CAR^{SHV}, and only has a positive influence on CAR^{SHV} when considered in interaction with functional product advantage. Additionally, the authors find that the interaction of symbolic value and functional product advantage has a negative influence on CAR^{SHV}.

The analyzed event (unveiling of the product's visual appearance) is clearly related to the sample firms' core business operations and consumers' perceptions of product design dimensions may influence the value of the operating business. However, they do not influence the firms' non-operating assets and debt.

6.2. First step: calculating the average value of the event

To the data that the authors have kindly provided us with (CAR^{SHV}, all independent variables, event dates, and firm names), we added firms' leverage effects, which we calculated using data on shareholder value, non-operating assets and debt from Compustat and CRSP (for Compustat Data Items used to calculate the leverage effect see Appendix A).

The average leverage effect for the sample was 2.19 with a standard deviation of 1.66, resulting in an average cross-firm variation coefficient of 0.76. This average leverage effect is higher than the overall average leverage effect of the firms listed in the S&P Total Market Index (1.54, see Appendix A). Still, 17% of firms in the sample featured leverage effect values smaller than 1 (i.e., more non-operating assets than debt). The lowest value for the leverage effect in the sample is 0.66; the highest is 9.37. Thus, the impact of the observation with the highest leverage effect on the calculation of the event's average value is about 14.2 times higher (9.36/0.66) than the impact of the observation with the lowest leverage effect. Furthermore and importantly, we find a correlation of −0.27 between CAR^{OB} and the leverage effect.

In our analysis, we first replicate their results and then replace their dependent variable CAR^{SHV} by CAR^{OB}. This analysis shows that the sample's average CAR^{SHV} is 1.28%, and the average CAR^{OB} is 1.13%. Thus, the sample's average CAR^{SHV} is 13.27% higher than its average CAR^{OB}. This result is in line with expectations, as we expect absolute CAR^{SHV} to be larger than absolute CAR^{OB} because the sample's average leverage effect is >1 (see also Table 1). In monetary terms the 13.27% represent $75 million for all firms in the sample and an average of $0.9 million per firm. The parametric *t*-test shows that both CAR^{SHV} ($t = 3.87$, $p < 0.01$) and CAR^{OB} ($t = 3.79$, $p < 0.01$) are significantly different from zero. In line with this finding the non-parametric Wilcoxon signed-rank test rejects the null hypothesis of zero abnormal returns for both CAR^{SHV} ($Z = 3.57$, $p < 0.01$) and CAR^{OB} ($Z = 3.37$, $p < 0.01$); a generalized sign test also rejects the null hypothesis of zero abnormal returns at the 5% level.

6.3. Second step: explaining differences in event value

Our first regression (Model I in Table 6) replicates their results. It uses CAR^{SHV} as the dependent variable, together with the following independent variables: aesthetic, ergonomic, and symbolic value, functional product advantage and interactions of these three design dimensions with functional product advantage. We also control for brand familiarity, firm size and industry. Next, we rerun the regression using CAR^{OB} instead of CAR^{SHV} as the dependent variable (Model II). Table 6 reports the results.

In contrast to the regression using CAR^{SHV} as the dependent variable (Model I), the regression with CAR^{OB} as the dependent variable (Model II) confirms all the theoretically expected effects. The significance levels associated with the effects identified in

Table 6
Comparison of results for CAR^{SHV} and CAR^{OB} as dependent variables.

Variables	Regressions					
	Model I CAR^{SHV}			Model II CAR^{OB}		
	β	t		β	t	
Functional product advantage	0.41	3.13	**	0.27	2.16	*
Aesthetic value	0.33	1.60		0.52	2.32	**
Ergonomic value	0.26	2.04	*	0.29	−3.14	*
Symbolic value	−0.43	−2.12	*	−0.61	3.36	**
Aesthetic value × functional product advantage	0.31	2.09	*	0.49	3.36	**
Ergonomic value × functional product advantage	0.00	0.01		−0.01	−0.10	
Symbolic value × functional product advantage	−0.28	−2.04	*	−0.42	−3.10	**
CV: industry	−0.13	−1.01		−0.08	−0.67	
CV: firm size	−0.19	−1.98		−0.28	−2.99	**
CV: brand familiarity	−0.41	−3.51	**	−0.25	−2.23	*
R^2	0.49			0.52		
Adj. R^2	0.41			0.45		
N	83			83		

CV: control variable. Independent variables are mean-centered to enhance the interpretability of the results.
* $p < 0.05$.
** $p < 0.01$.

the regression using CAR^{SHV} are either the same or greater in the regression using CAR^{OB}. Even more importantly, aesthetic value has a highly significant positive effect in the regression using CAR^{OB}.

Hence, when carrying out marketing-related event studies, using CAR^{OB} as the dependent variable can enable the researcher to detect underlying relationships between the event characteristics and financial return that might not be observable when CAR^{SHV} is used as the dependent variable. Importantly, our results show that using CAR^{OB} instead of CAR^{SHV} as the dependent variable can yield much more nuanced insights on how marketing creates value, which in turn has direct and managerially relevant implications for the allocation of (here design-related) investments.

7. Second empirical study: reanalysis of a prior event study conducted by Kulkarni et al. (2003)

7.1. Description of event study

The second event study we reanalyze is by Kulkarni et al. (2003). In their study, the authors examine possible reasons for firing advertising agencies and relate these reasons to the stock price consequences using an event study. The reasons they consider include decline in sales, market share, and profitability in the period preceding the firing. Thus, the event "firing the advertising agency" is assumed to be the result of a decline in the advertiser's operating business, for which the firm attributed responsibility to the advertising agency. This type of event is of a tactical nature and may influence the value of the operating business through a change in advertising activities. Additionally, there is no compelling theory why the firing of an advertising agency should influence the value of a firm's non-operating assets and debt (e.g., Cochrane, 2005; Elton et al., 2001).

Kulkarni et al. (2003) calculate five regressions using CAR^{SHV} as the dependent variable and industry-adjusted measures for growth in sales and return on equity as independent variables. They find that the only variable that explains the variability in abnormal returns is the industry-adjusted growth rate in sales (i.e., growth in market share) over the medium term. Thus, they conclude that investors interpret the firing of an advertising agency as a managerial confirmation of a loss in market share, not as a corrective action that can remedy a sales growth problem. They base their interpretation on their finding that firms that engaged in advertising ("advertisers") and whose market shares increased, achieved high abnormal returns, whereas advertisers that experienced a decrease in market share had low or negative abnormal returns.

7.2. First step: calculating the average value of the event

Again, we used the data the authors kindly provided us with (CAR^{SHV}, all independent variables, event dates, and firm names) and collected the additional data that we needed to calculate the firms' leverage effects (i.e., data on shareholder value, non-operating assets and debt from Compustat and CRSP).

The average leverage effect for the sample was 1.08 with a standard deviation of 0.26, resulting in an average cross-firm variation coefficient of 0.24. This average leverage effect is much lower than the overall average leverage effect of the firms listed in the S&P Total Market Index (1.54, see Appendix A). 24% of the firms in the sample featured leverage effect values smaller than 1 (i.e., more non-operating assets than debt). The lowest value for the leverage effect in the sample is 0.86; the highest is 2.12. Thus, the impact of the observation with the highest leverage effect on the calculation of the event's average value is about 2.5 times higher (2.12/0.86) than the impact of the observation with the lowest leverage effect. Furthermore, we find a correlation between CAR^{OB} and the leverage effect of 0.14.

Our reanalysis shows that the sample's average CAR^{SHV} is −0.66%, and the average CAR^{OB} is −0.74%. Thus, the sample's average CAR^{OB} is 12.12% lower than its average CAR^{SHV}. In monetary terms the 12.12% represent $60.5 million for all firms in the sample and an average of $1.7 million per firm. However, on the basis of a parametric *t*-test neither CAR^{SHV} nor CAR^{OB} are significantly different from zero. Furthermore, the non-parametric Wilcoxon signed-rank test and a generalized sign test fail to reject the null hypothesis of zero abnormal returns for both CAR^{SHV} and CAR^{OB}.

That the sample's average CAR^{OB} is lower than its average CAR^{SHV} may seem surprising, as we might expect absolute CAR^{SHV} to be larger than absolute CAR^{OB} because the sample's average leverage effect is >1 (see also Table 1). Note, however, that Table 1 makes statements about the relationships among CAR^{SHV}, CAR^{OB}, and the leverage effect for each firm-instance observation, but not for the whole sample. The reason for this result stems from the size of the CAR^{OB} for the 24% of firms whose leverage effects are smaller than 1: For negative CAR^{OB}, the average absolute value of CAR^{OB} is 73% larger than the sample mean. For positive CAR^{OB}, the average absolute value of their CAR^{OB} is 22% smaller than the sample mean. As the leverage effect deflates the impact of these observations featuring very low values (i.e., below average negative values, below average positive values), the average CAR^{SHV} > average CAR^{OB} ($|CAR^{OB}| < |CAR^{SHV}|$).

7.3. Second step: explaining differences in event value

We replicate the fifth and pivotal regression reported by Kulkarni et al. (2003), see their Table 4). The regression uses CAR^{SHV} as the dependent variable, together with the following independent variables: industry-adjusted growth rate in sales (i.e., growth in market share) over a medium term (SG4-IA), industry-adjusted return on equity (ROE-IA), and the interaction between SG4-IA and ROE-IA (Model I in Table 7). After the replication, we recalculate the regression using CAR^{OB} instead of CAR^{SHV} as the dependent variable (Model II). Table 7 reports the results.

Table 7
Comparison of results for CAR^{SHV} and CAR^{OB} as dependent variables.

Variables	Regressions			
	Model I CAR^{SHV}		Model II CAR^{OB}	
	Coeff	S.E.	Coeff	S.E.
Intercept	−0.01	0.01	−0.01	0.01
SG4-IA	0.09	0.04*	0.08	0.04
ROE-IA	0.02	0.03	0.02	0.03
ROESG4	−0.03	0.04	−0.03	0.04
R^2	0.21		0.20	
Adj. R^2	0.14		0.13	
N	36		36	

SG4-IA is the industry-adjusted growth in sales from quarter 4 to quarter 1; ROE-IA is the industry-adjusted return on equity; ROESG4 is the interaction between ROE-IA and SG4-IA.
* $p < 0.05$.

Kulkarni et al. (2003) attribute decreases in advertisers' share prices to decreases in market shares observed over a medium term preceding the firing of the advertising agency. They base this interpretation on the results of the regression model replicated in Table 7 (Model I). The coefficient of the market share over a medium term (SG4-IA) is significant at the 5% level. However, using CAR^{OB} as the dependent variable, as in Model II in Table 7, causes the coefficient of the market share to decline slightly. Importantly, the significance of the market share coefficient also disappears.

This reanalysis of the results published by Kulkarni et al. (2003) shows that when CAR^{OB} is used as a dependent variable instead of CAR^{SHV}, different coefficients are obtained, and the significance of the coefficient of the central variable, market share, disappears when we use CAR^{OB} instead of CAR^{SHV} as the dependent variable. The importance of using CAR^{OB} instead of CAR^{SHV} becomes even more obvious when we consider that the leverage effect of the sample in this study was only 1.08 with a very moderate standard deviation (0.26) as well as a moderate cross-firm coefficient of variation (0.24). Furthermore, the correlation between CAR^{OB} and the leverage effect is moderate, at only 0.14.

8. Third empirical study: reanalysis of a prior event study conducted by Karpoff and Rankine (1994)

The third event study we reanalyze is by Karpoff and Rankine (1994). In this study, the authors examine the stock price reaction to the announcement of a company name change. In line with prior research by Horsky and Swyngedouw (1987), Argenti, Hansen, and Neslin (1988) and Bosch and Hirschey (1989) they expect to find a positive effect of a company name change on CAR^{SHV}.[10] As the authors explain, they expect such a positive effect for two reasons: First, a company name change conveys information about the firm's product lines. In particular, a name change can reflect a change into a new or broader product line and/or gives the firm the flexibility to expand into new product lines in the future. Second, a company name change conveys favorable information about the firm's future performance. Specifically, managers hope to "improve the firm's recognition in the investment community" (Wall Street Journal, 1980) and to "affect the firm's operations favorably by providing the firm with a common identity […] which will eventually affect labor productivity and cash flows" (Karpoff & Rankine, 1994). As these theoretical considerations illustrate, a company name change may influence the value of the firm's operating business, but not non-operating assets and debt.

Karpoff and Rankine (1994) analyzed whether CAR^{SHV} is significantly different from zero for different subsamples of their data set. They found that the evidence of a positive stock price reaction to the announcement of a company name change is rather weak and sensitive to sample selection. Therefore, the authors suggest being cautious with statements about the positive valuation effects of corporate name changes.

Again, the authors kindly provided us with their data set of 147 name change announcements that were made in the Wall Street Journal (WSJ) from 1979 to 1987. The data set comprises information on the CAR^{SHV} calculated over a two-day event window, the event dates (i.e., announcement in Wall Street Journal), the firms that changed their names, and a dummy variable indicating whether the company name change was mentioned or proposed in a proxy statement before the WSJ announcement.[11] With these data, we were able to verify the authors' key statement that CAR^{SHV} is only positive and significant over the two-day event window in the subsample that comprises those company name changes that were not mentioned or proposed in a proxy statement before the WSJ announcement. Across all observations of the total sample, the authors find that CAR^{SHV} is positive, but insignificant.

To the authors' data, we added the data that we needed to calculate the firms' leverage effects. Our final sample comprises 110 name change announcements. We lose 37 observations compared to Karpoff and Rankine's original sample, because 10 firms are no longer listed on Compustat/CRSP and 27 firms miss data on at least one of the variables required to calculate the leverage effect. Reassuringly, Karpoff and Rankine's results are essentially unchanged when replicated using the sample of 110 observations.

[10] Karpoff and Rankine (1994) call CAR^{SHV} "cumulated average forecast error".
[11] Unfortunately and probably due to the fact that the original study was conducted before >20 years, not all the variables used in the paper were available in the data set or could be retrieved from the databases in WRDS. We were able to reconstruct subsamples A, B, and D described in Table 1 of Karpoff and Rankine (1994).

The average leverage effect for the sample is 1.80 with a standard deviation of 1.02, resulting in an average cross-firm variation coefficient of 0.57. This average leverage effect is higher than the overall average leverage effect of the firms listed in the S&P Total Market Index (1.54, see Appendix A). Still, about 13% of firms in the sample featured leverage effect values smaller than 1 (i.e., more non-operating assets than debt). The lowest value for the leverage effect in the sample is 0.40; the highest is 6.78. Thus, the impact of the observation with the highest leverage effect on the calculation of the event's average value is about 17 times higher (6.78/0.40) than the impact of the observation with the lowest leverage effect. Furthermore, we find a correlation of 0.15 between CAR^{OB} and the leverage effect.

Our reanalysis shows that the overall sample's average CAR^{SHV} is 0.58%, and the average CAR^{OB} is −0.01%. In monetary terms this difference represents $28 million for all firms in the sample and an average of about $0.3 million per firm. On the basis of a parametric *t*-test neither CAR^{SHV} nor CAR^{OB} are significantly different from zero. Furthermore, the non-parametric Wilcoxon signed-rank test and a generalized sign test fail to reject the null hypothesis of zero abnormal returns for both CAR^{SHV} and CAR^{OB}. Although neither CAR^{SHV} nor CAR^{OB} are significantly different from zero, this example illustrates that the heterogeneity in the firms' leverage effects, which inflates the impact of observations pertaining to firms with large debt and deflates those pertaining to firms with large non-operating assets, can provide misleading evidence regarding the sign of the event's impact. In this study's sample, the positive correlation between the leverage effect and the event value (CAR^{OB}) indicates that firms with high debt have greater event values. The observations pertaining to these firms are more heavily weighted in the calculation of CAR^{SHV}, which is why $CAR^{SHV} > CAR^{OB}$ and why the two variables even differ in their signs.

Like Karpoff and Rankine (1994), we split the sample into two subsamples. The one subsample comprises all firms whose name changes were mentioned or proposed in the Wall Street Journal for the first time. Thus, investors could not have become aware of the company name change before the event date (i.e., the announcement in the Wall Street Journal). The other subsample comprises all the other firms whose name changes were mentioned or proposed in a proxy statement before the announcement in the Wall Street Journal. As shown in Table 8, we find that both CAR^{SHV} and CAR^{OB} are positive and significantly different form zero only in the subsample of firms whose name changes were mentioned or proposed in the Wall Street Journal for the first time. For the other subsample, we do not find any significant effects. Thus, our analysis confirms Karpoff and Rankine's results.

9. Summary and conclusion

Marketing-related events frequently influence only the value of the operating business, but not non-operating assets and debt. Examples of such marketing-related events are the unveiling of a new product's appearance, the firing of advertising agencies, and company name changes. We argue that event studies designed to analyze the effects of such events should use CAR^{OB} as their dependent variable instead of CAR^{SHV}, which is currently used. The derivation of CAR^{OB} is straightforward: CAR^{SHV} is first determined as in traditional event studies and then simply divided by the leverage effect, which, in turn, can be calculated using just three publicly-available variables.

The reanalysis of three previously published marketing event studies as well as our simulation study show that ignoring the firm-specific leverage effects influences an event study's results in unpredictable ways. Table 9 summarizes the results of our reanalysis of the three previously published marketing event studies.

We want to emphasize that it is up to the researchers who conduct an event study to justify their choice of the dependent variable. The interviews that we conducted with industry experts suggest that investors and analysts do not adjust non-operating assets and debt in their valuation models following marketing events. Instead, they only adjust the value of a firm's operating business. In general, we argue that the more likely an event impacts the firm's risk structure or financial needs above and beyond its working capital, the more researchers should consider an impact of the event on non-operating assets and debt as well. The reason is that for these kinds of events, at least theoretically, we cannot exclude an impact on debt (e.g., through impact on firm's credit rating) or non-operating assets (e.g., alternative use of excess cash with different return) ex ante. Researchers might also consider

Table 8
One-sample *t*-test and descriptive statistics for CAR^{SHV} and CAR^{OB} for different subsamples.

	Mean	SD	n	Comparison Value	t	df
Total sample						
CAR^{SHV}	0.58%	0.05	110	0	1.33	109
CAR^{OB}	−0.01%	0.04	110	0	−0.03	109
Name change announced in WSJ for the first time						
CAR^{SHV}[a]	1.20%	0.04	57	0	2.16*	56
CAR^{OB}[a]	0.85%	0.03	57	0	2.01*	56
Name change announced in proxy statement before WSJ						
CAR^{SHV}	−0.09%	0.05	53	0	−0.14	52
CAR^{OB}	−0.93%	0.04	53	0	−1.58	52

SD = Standard deviation. df: degrees of freedom.

* $p < 0.05$.

[a] Non-parametric Wilcoxon signed-rank test rejects the null hypothesis of zero abnormal returns at 10% level for both CAR^{SHV} ($Z = 1.88$, $p < 0.10$) and CAR^{OB} ($Z = 1.67$, $p < 0.10$); a generalized sign test also rejects the null hypothesis of zero abnormal returns at the 10% level.

Table 9
Summary of reanalysis of previously published marketing event studies.

	Bornemann et al. (2015)	Kulkarni et al. (2003)	Karpoff and Rankine (1994)
Average leverage effect	2.19	1.08	1.80
Average cross-firm variation coefficient of leverage effect	0.76	0.24	0.57
Share of firms with leverage effect <1	17%	24%	13%
Lowest value of leverage effect	0.66	0.86	0.40
Highest value of leverage effect	9.37	2.12	6.78
Ratio of highest to lowest value of leverage effect	14.20	2.47	16.95
Percentage difference between average CAR^{SHV} and average CAR^{OB}	CAR^{SHV} is 13.27% higher than CAR^{OB}	CAR^{OB} is 12.12% lower than CAR^{SHV}	CAR^{SHV} and CAR^{OB} differ in sign
Correlation between CAR^{OB} and leverage effect	−0.27	0.14	0.15
Substantive insight	Insignificant effect turns into significant effect (second step of event study)	Significant effect turns into insignificant effect (second step of event study)	CAR remains insignificant but differs in sign (first step of event study)

reporting results for both models, i.e. one using CAR^{OB} and another using CAR^{SHV}, and then argue which one is most suitable for the problem at hand.

The choice of the dependent variable is particularly important when comparing marketing performance across firms. As shown in our numerical example and the reanalysis of prior event studies, results obtained in cross-sectional studies using CAR^{OB} instead of CAR^{SHV} are likely to differ. The reason is that ignoring the differences in firm-specific leverage effects inflates the impact of observations pertaining to firms with large debt and deflates those pertaining to firms with large non-operating assets. Such biases can influence a study's conclusions regarding the size of the impact of a marketing-related event and, even worse, can provide misleading evidence regarding the sign of the impact: value-creating events can easily be classified as value-destroying events and vice versa.

Appendix A. Size of variation of leverage effect

In this Appendix, we analyze the differences in firms' leverage effects to show how ignoring these leverage effects influences the weights of firms' observations in the calculation of average values of CAR^{SHV}. As event studies usually use multiple observations per firm that are then compared among firms, we analyze (i) the within-firm variation of the leverage effect over time, and (ii) the variation of the leverage effect across firms. Kindly note that this analysis differs from Schulze et al.'s (2012) study in so far as we use a larger sample and focus on the variation of the leverage effect instead of its average size.

We use Compustat data to analyze firms listed in the S&P Total Market Index. Our unbalanced panel comprises 62,012 firm-year observations of 4903 firms from 17 years (1998 to 2014). We follow Eq. (2) and calculate the leverage effect as shareholder value (Compustat Data Item (CDI): prcc_f × csho (i.e., share price × common shares outstanding)) minus non-operating assets

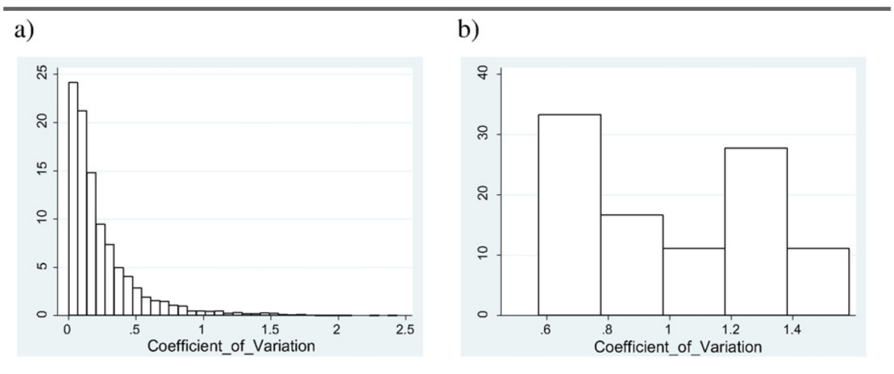

Fig. 3. Histograms of within-firm and cross-firm variations of leverage effects. a) Histogram of Within-firm Variations of Leverage Effects over Time. Average value of variation coefficient: 0.25, SD of variation coefficient: 0.28, N = 4,461 firms (442 firms were dropped because only 1 year of data was available). b) Histogram of Cross-Firm Variations of Leverage Effects (1998–2014). Average value of variation coefficient: 1.21, SD of variation coefficient: 0.55, N = 17 years.

(CDI: ivst (i.e., short-term investments)) plus total debt (CDI: dd1 + dltt + pstk (i.e., long-term debt due in one year + long-term debt + preferred stock)), divided by shareholder value (see Schulze et al., 2012).

We find that the average leverage effect across firms and across years is 1.54 with a standard deviation of 1.90. We fit the leverage effects of the 4903 firms (1998–2014) to various distributions (e.g., Log-Normal, Log-Logistic, Logistic, inverse Gaussian, Gamma, Normal) and find that a Log-Logistic distribution (scale parameter = 4.41, shape parameter = 1.22) best fits the empirical data (fit was measured using the Akaike Information Criterion).

Fig. 3a here provides a histogram of the 4903 within-firm variations of the leverage effect over time. We measured variation using the coefficient of variation, which is the ratio of the standard deviation to the mean. The average value of the variation coefficient is 0.25 (SD = 0.28). Fig. 3b provides a histogram of the variations of the leverage effects across firms for the 17 years. The average value of the variation coefficient is 1.21 (SD = 0.55) and is much larger than the value of the variation coefficient obtained in the within-firm analysis (0.25). This finding indicates that when carrying out an event study to examine an event that solely impacts firms' operating businesses, ignoring leverage effects is less problematic in within-firm analysis than in cross-firm analysis.

In the cross-firm analysis, the average values for the lowest and highest ventiles (top 5% and bottom 5%) in 2014 were, respectively, 0.84 and 2.67. Thus, for an event that has an effect of +1% on the value of the operating business, CAR^{SHV} would be 2.67% for a highly leveraged firm, whereas CAR^{SHV} would be 0.84% for an unleveraged firm. Hence, CAR^{SHV} of the highly leveraged firm is more than three times larger than the CAR^{SHV} of the unleveraged firm, which means that the CAR^{SHV} value corresponding to the highly leveraged firm receives more than three times higher weight in the calculation of the average CAR^{SHV}.

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