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# How do strategic alliance formations create shareholder value? An application of the event study methodology in the B2B context


Mariia Koval

Grenoble Ecole de Management

12 Rue Pierre Semard, 38000 Grenoble, France

Mariia.Koval@grenoble-em.com

Ghasem Zaefarian

Leeds University Business School, University of Leeds

Maurice Keyworth Building, Leeds, LS2 9JT, United Kingdom

G.Zaefarian@leeds.ac.uk

Viacheslav Iurkov

Grenoble Ecole de Management

12 Rue Pierre Semard, 38000 Grenoble, France

Viacheslav.Iurkov@grenoble-em.com

**Abstract**

By announcing the formation of business-to-business (B2B) relationships, such as strategic alliances, firms send signals to market observers who form expectations about these firms' future performance, ultimately affecting their shareholder value. The use of an event study methodology enables scholars to gauge the extent of the shareholder value these relationships can create. The role of the present study is twofold. First, we aim to systematically investigate the relationship between strategic alliance formations and firm shareholder value, identifying conditions under which strategic alliances create or even destroy value, including factors related to the firms and alliances as well as their interactions. Our second objective is to explain how B2B marketing researchers can apply the event study methodology in the context of strategic alliances. We provide a detailed explanation of how scholars can apply an event study methodology to strategic alliances, and B2B relationships more broadly, taking into account the research area-specific considerations, such as the appropriate modeling approach, variable coding, and event and estimation windows.

**Keywords:** event study methodology; strategic alliance formation; shareholder value

## 1. Introduction

Strategic alliances are business-to-business (B2B) relationships in which firms collaborate to develop new products, strengthen their supply chains, or enter new markets (Chakravarty, Zhou, & Sharma, 2020; Spekman, 2012; Swaminathan & Moorman, 2009; Xiong & Bharadwaj, 2011), with the potential to create shareholder value. For example, Pfizer's shareholder value increased when it announced a strategic alliance with BioNTech to accelerate global COVID-19 vaccine development in April 2020[1] and when the companies reported that their vaccine candidate achieved success in the first interim analysis from Phase 3 study in November of the same year[2] (Piñeiro-Chousa, López-Cabarcos, Quiñoá-Piñeiro, & Pérez-Pico, 2022). However, prior research on the role of strategic alliances in firm shareholder value has yielded mixed findings (Das, Sen, & Sengupta, 1998; Fang, Lee, Palmatier, & Han, 2016; Fang, Lee, & Yang, 2015; Swaminathan & Moorman, 2009), calling for a comprehensive study to explore the potential of strategic alliances in creating shareholder value under different conditions.

When examining the value creation potential of alliance formation announcements, some B2B marketing scholars have utilized the event study methodology that allows for the inference of cause and effect in a controlled quasi-experimental setting (Fang et al., 2016; Fang et al., 2015; Srinivasan & Hanssens, 2009; Swaminathan & Moorman, 2009). The event study methodology involves comparing a firm's observed stock return on the day of an alliance announcement with the expected return if the event had not occurred, leading to what is known as an abnormal stock return representing the shareholder value of the alliance (Fama, Fisher, Jensen, & Roll, 1969). In a recent study, Ullah, Zaefarian, Ahmed, and Kimani (2021) provided a comprehensive step-by-

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[1] Accessible through Pfizer's press release portal: https://www.pfizer.com/news/press-release/press-release-detail/pfizer-and-biontech-announce-further-details-collaboration
[2] Accessible through Pfizer's press release portal: https://www.pfizer.com/news/press-release/press-release-detail/pfizer-and-biontech-announce-vaccine-candidate-against

step guide to conducting event studies in marketing. However, when applying the event study methodology in the context of B2B relationships, researchers and practitioners should carefully consider specific methodological aspects unique to this area of research. For instance, as alliance research data typically involve both firm- and alliance-specific information, an appropriate modeling approach, such as hierarchical linear modeling (HLM), may be required (Aguinis, Gottfredson, & Culpepper, 2013). While Ullah et al. (2021) explained in detail how to calculate the abnormal stock return for a specific event, they primarily focused on the immediate stock market reaction to an event. However, the event study methodology also permits the calculation of long-term effects on the stock market. Understanding how to estimate these long-term effects is relevant in B2B relationship settings where strategic alliances may significantly impact firms' long-term value and competitiveness in the market (e.g., Sadovnikova & Pujari, 2017). Unfortunately, only a limited number of studies have touched upon the long-term value-creation effects of strategic alliances (Sadovnikova & Pujari, 2017; Swaminathan & Moorman, 2009).

Building on the alliance literature and the work by Ullah et al. (2021), this paper sets the two research objectives: to systematically investigate the relationship between strategic alliance formations and firm shareholder value, identifying conditions under which strategic alliances create (or even destroy) value, and to explain how B2B marketing researchers can apply the event study methodology in the context of alliances. Specifically, we discuss common alliance databases, methods for coding variables extracted from these databases, procedures for deriving abnormal stock returns following alliance announcements, and modeling techniques to address dependencies in alliance data. Importantly, we provide guidelines on how to use the event study methodology to assess the long-term shareholder value effects of strategic alliance announcements. We also discuss the advantages and disadvantages of this methodology in calculating long-term effects. Subsequently, we apply the event study methodology to we examine which alliance- and firm-level factors result in higher shareholder value following alliance announcements and conduct an exploratory analysis to identify statistically significant cross-level interactions. Our study employs a two-level HLM model based on an extensive dataset covering alliance formations during 1990-2020.

Our study makes several important contributions to B2B marketing research and practice. First, it contributes to marketing literature on strategic alliance formations (e.g., Das et al., 1998; Fang et al., 2016; Fang et al., 2015; Swaminathan & Moorman, 2009) by providing a comprehensive view of the conditions under which strategic alliances enhance a firm's shareholder value. The merit of our study is the encouragement of B2B scholars to focus on the most promising types of strategic alliances in terms of value creation potential and to explore relevant research questions concerning such alliances. Equally important, our exploratory analysis has identifies conditions under which strategic alliances may deteriorate value. Second, building on the methodological study by Ullah et al. (2021), our work extends their research by discussing how B2B scholars should appropriately apply the event study methodology in the alliance context, taking into account methodological considerations pertaining to alliance research. Importantly, we introduce a procedure for deriving long-term shareholder value effects using the event study methodology and demonstrating its application in the strategic alliance context. Our study also provides recommendations to practitioners regarding the formation of strategic alliances that receive more positive evaluations from investors, given various alliance- and firm-level characteristics.

**2. Overview of event study methodology applications in B2B literature**

Strategic alliances gained popularity approximately three decades ago (Gulati, 1998; Hagedoorn, 2002). Since then, scholars have utilized the event study methodology to study whether and how strategic alliances contribute to shareholder value. Koh and Venkatraman

(1991) were among the earliest studies to report that announcements of equity alliances (joint ventures) led to a positive stock market reaction. Consequently, event studies extended this line of inquiry to contractual strategic alliances. Das et al. (1998) were among the first to study abnormal stock returns for technological and marketing alliances. Das and colleagues utilized a sample of 119 strategic alliance announcements formed during 1987-1991 obtained from an Information Technology Strategic Alliances database. They matched data on alliance announcements with the corresponding partnering firms' daily stock return data from the Center for Research in Security Prices (CRSP) files and firm financials from the COMPUSTAT database. Das et al. (1998) relied on the market return model to estimate the expected stock return from the alliance announcement. The expected stock return is a linear function of the observed stock return on the alliance announcement-event day. They used the 200 trading days ending ten days before an alliance announcement to estimate the parameters of the market return model, and the event window of up to seven days centered around the reported alliance announcement day in the Wall Street Journal or the Financial Times (day 0). In other words, they allowed for information leakage before an alliance announcement and for a slow market reaction to an announcement within the three days before and the three days after the announcement was reported.

Consequently, research in marketing started to include more alliance- and firm-level variables to explain abnormal stock returns from alliance announcements and to employ other ways of estimating these returns. For example, Swaminathan and Moorman (2009) conducted an event study of 230 marketing alliance announcements in the software industry during 1988-2005. Swaminathan and Moorman (2009) collected data on strategic alliance announcements from the SDC Platinum database (the Joint Ventures & Strategic Alliances module), which provides descriptions of alliances and their participants. Similarly to Das et al. (1998), stock returns were obtained from the CRSP database, and firm-specific information was obtained from COMPUSTAT. The authors calculated firm abnormal returns using the conventional market return model and additionally ran a more sophisticated Carhart-modified Fama-French model (Carhart, 1997), also known as the four-factor model. The four-factor model extends the market model by including three additional factors to estimate abnormal stock returns. Specifically, in addition to the return on the market index (e.g., CRSP equally-weighted or value-weighted index), the model includes the return differential between portfolios of small and large market capitalization stocks, the differential between portfolios of high-(value) and low-(growth) book-to-market ratio stocks and the differential between portfolios of high- and low-prior-return stocks. They estimated the models using daily stock returns data for each firm from 240 days ending ten days before the alliance announcement-event day. The authors calculated the cumulative abnormal stock returns for different event windows (10 days before the event to 10 days after the event). They tested their significance using a t-statistic described in Brown and Warner (1985). The test showed that the most significant t-statistic was for the event window of two days before the event and one day after the event day. In addition to looking at the immediate stock market reaction to marketing alliance announcements, the authors also examined the long-term effects, however, they were not found to be significant.

Building on Swaminathan and Moorman (2009), Fang et al. (2015) examined strategic alliances between upstream biotech firms and downstream pharmaceutical firms to co-develop new products. The authors studied how the timing of such co-development influences partnering firms' value due to their alliance formation. Fang and colleagues employed an event study of 276 co-development agreements during 1998-2010. The alliance data were collected from Deloitte Recap—a database containing detailed information on the firms in the biotech and pharmaceutical industries, including their alliances. Like Swaminathan and Moorman (2009), Fang et al. (2015) relied on the market return model to estimate the stock returns following alliance announcements using daily stock data from the CRSP database and 240 days ending ten days before the event day. They also selected the event window with the most significant t-statistics, namely, two days before the event day to one day after the event day. Fang et al. (2015) also adopted the four-factor model to estimate abnormal stock returns as a robustness check.

In another alliance study, Fang et al. (2016) used an event study methodology to analyze whether a dyadic (involving two partners) or plural (involving more than two partners) alliance structure generates more shareholder value for partnering firms, using a sample of 928 marketing alliances from 213 firms in high-tech manufacturing industries during 1998-2010. Similarly to Swaminathan and Moorman (2009), Fang et al. (2016) relied on the SDC Platinum database to collect information on strategic alliances, COMPUSTAT to obtain firm-specific information, and CRSP for daily stock return data. The authors used the same approach to estimating the stock returns and calculating the abnormal returns as in Fang et al. (2015).

In a more recent study, Cao and Yan (2017) examined how partnering firms can benefit from announcing a brand alliance (i.e., the short-term or long-term combination or association of several individual brands) depending on brand value and other brand characteristics. Oh, Lee, and Kim (2018) studied how a partner’s customer satisfaction determined the focal firm's shareholder value from a marketing alliance. Pasirayi (2020) looked at shareholder value from store-in-store agreements (i.e., in which so-called housing retailers lease their in-store space to other retailers) generated by the housing retailers. Truong, Ludwig, Mooi, and Bove (2022) utilized the event study methodology to examine how contractual terms and formulations shaped investor reactions to technology licensing contract announcements. These studies used an approach similar to Swaminathan and Moorman (2009) to estimate stock returns following contact announcements.

The SDC Platinum database, LexisNexis, or similar business news databases such as Factiva were used to collect data on B2B relationships.

Contrary to the majority of event study applications in B2B literature that only looked at the immediate stock market reaction to B2B relationship formations, Sadovnikova and Pujari (2017) also examined the long-term effects of marketing and technological green partnerships using two alternative estimation approaches, namely, the buy-and-hold abnormal returns approach and the calendar-time portfolio returns. Due to a relatively small sample size, the authors utilized a one-year horizon.

Table 1 provides a summary of the discussed studies.

-----Insert Table 1 about here-----

## 3. Key considerations in conducting event studies in alliance research

### 3.1. Types of alliance events

B2B marketing researchers have primarily examined alliance formation events using the event study methodology (e.g., Fang et al., 2016; Fang et al., 2015; Swaminathan & Moorman, 2009). When studying such events, scholars should carefully distinguish between alliances announced solely by partnering firms from those completed (Schilling, 2009). The status of an alliance is often available in dedicated alliance databases, such as SDC Platinum, and can be additionally verified through news databases, such as LexisNexis and Factiva. Suppose researchers are interested in studying alliances that were indeed formed rather than ones for which negotiations did not lead to deal completion. In that case, the focus should normally be on completed alliances. Announced but not completed alliances might need to be additionally verified for their completion in the news databases.

Certainly, alliance development does not involve only alliance formation and termination stages. In practice, alliances go through a substantial maintenance period. During this period, partnering firms may succeed or experience failures in pursuing common goals, such as joint product development and commercialization. However, it is challenging for researchers to study the events during the alliance maintenance period as partnering firms rarely report them. Thus, such information will not be available in a majority of cases. What is sometimes available is the alliance termination date. One can distinguish between planned and unplanned alliance terminations (Koval, 2021; Pangarkar, 2009). Often, scholars are more interested in studying unplanned alliance terminations associated with adverse events and alliance instability that provoked the end of an alliance. On the contrary, planned alliance terminations refer to situations when alliance contracts have naturally expired, or partnering firms have completed the alliance goal. Planned terminations do not imply significant tensions in the alliances, making them less interesting to study.

### 3.2. Data sources for alliance events

When examining alliance formation events, scholars rely on several widely used data sources, such as the SDC Platinum database. The event can also be extracted manually from business news databases, such as Factiva and LexisNexis, or firms' press releases. Industry-specific alliance databases, such as Cortellis Deal Intelligence, cover the biopharmaceutical industry. SDC Platinum is perhaps the most widely used database in marketing and management studies (Schilling, 2009; Zaefarian, Misra, Koval, & Iurkov, 2022). The "Joint Ventures & Strategic Alliances" module provides information on strategic alliances. Such data contains information on alliance formation and termination dates, if available, parties involved, alliance functions (e.g., research and development, marketing, manufacturing), an alliance organizational form (e.g., an equity joint venture), alliance and parties' geographic location and their correspondent industries, among others. In turn, business news databases such as Factiva and LexisNexis are the most comprehensive ones in terms of alliance events' coverage. Cortellis

Deals Intelligence is specialized for B2B scholars interested in strategic alliances in the biopharmaceutical industry (e.g., Arslan & Tarakci, 2022; Devarakonda, Reuer, & Tadikonda, 2022). It is previously known as the Thomson Reuters Recap database. Table 2 presents a summary of the main alliance databases.

-----Insert Table 2 about here-----

**3.3. Coding of main alliance characteristics**

Depending on the database that scholars use to collect alliance data, coding alliance variables may be challenging or straightforward. For example, SDC Platinum already reports all the information needed to code main alliance variables—the reason why it has probably gained wide popularity. In contrast, once scholars extract alliance data from business news databases such as Factiva and LexisNexis, they need to carefully investigate the alliance announcement texts and manually code alliance variables. Table 3 provides a summary of the main alliance variables, their operationalization, and data sources, primarily relying on the data available in SDC Platinum.

-----Insert Table 3 about here-----

**3.4. Modelling approaches to estimate abnormal stock returns**

**3.4.1. Cumulative abnormal stock return**

The dependent variable in the event studies is a firm's cumulative abnormal stock returns (CAR) due to an alliance event (Ullah et al., 2021). In alliance research (e.g., Fang et al., 2016; Fang et al., 2015; Swaminathan & Moorman, 2009), CAR is usually obtained using the conventional market model (Fama et al., 1969) and the Fama-French model modified by Carhart (1997) also known as the four-factor model.

*Market model.* The assumption behind the market model is that if one believes in an informationally efficient market, any new information firms disclose should be reflected in their stock prices. Hence, the value-creation potential of any disclosed event, such as an alliance announcement, can be assessed by studying the price changes surrounding the disclosed event. In alliance research, the abnormal stock market returns surrounding an alliance announcement (i.e., CAR) reflect the impact of such an event on firm value. The stock return, $r_{it}$, for firm $i$ on day $t$ is calculated as:

(1) $r_{it} = (p_{it} + d_{it} - p_{it-1})/p_{it-1}$, where $p_{it}$ ($p_{it-1}$) is the stock price for firm $i$ on day $t$ ($t - 1$) and $d_{it}$ is the dividend of firm $i$ on day $t$.

Similarly, $r_{mt}$, is calculated as the average of the stock returns of all firms in a given stock exchange. The measure of abnormal stock returns is the residual of the following market model:

(2) $r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}$, where $\alpha_i$ and $\beta_i$ are firm-specific parameters, $\varepsilon_{it}$ is independent and identically distributed (Brown & Warner, 1985), and $r_{it}$ and $r_{mt}$ are defined earlier.

To estimate the market model, one can use daily data on the stock market returns of each firm during a specific estimation window, the most common in alliance research being 240 days ending ten days before the event day (e.g., Das et al., 1998; Gulati, Lavie, & Singh, 2009; Lavie, Lunnan, & Truong, 2022; Swaminathan & Moorman, 2009). Then, one needs to use the estimates obtained from this model to predict the daily returns for each firm for the event day, $t$:

(3) $\hat{r}_{it} = \hat{\alpha}_i + \hat{\beta}_i r_{mt}$, where $\hat{r}_{it}$ is the predicted daily return and $\hat{\alpha}_i$ and $\hat{\beta}_i$ are model estimates.

The estimated prediction errors, $AR_{it} = r_{it} - \hat{r}_{it}$, during the alliance announcement obtained using the estimated parameters are the market model residuals or abnormal stock returns. Cumulative abnormal stock returns due to an alliance announcement are calculated as:

(4) $CAR_{it} = \sum_{t-k}^{t+q} AR_{it}$, where $AR_{it}$ is the abnormal return of firm $i$ on day $t$, $k$ and $q$ are the number of days before and after the event day, $t$.

One should therefore set up an event window surrounding the alliance announcement day reported in the media and aggregate the abnormal returns over the event window. On the one hand, the chosen event window should be sufficiently long to account for disseminating information regarding the alliance announcement over time. On the other hand, long event windows increase the likelihood of firms reporting other events that may reduce the impact of the focal alliance announcement on firm value (Sorescu, Warren, & Ertekin, 2017; Thomaz & Swaminathan, 2015). For example, one can calculate the cumulative average abnormal returns for various windows (e.g., three days before and after the event date) and test the significance of each event window using the t-statistic, as in Brown and Warner (1985). One can also proceed by calculating the Patell (1976) z-statistic for the cumulative abnormal stock returns for different event windows (e.g., Mooi & Wuyts, 2021; Raassens, Wuyts, & Geyskens, 2012). Brown and Warner (1985) conclude from their specification tests that "standard parametric tests for significance of the mean excess return are well-specified," and these tests "typically have the appropriate probability of Type I error" (p. 25). In alliance research (e.g., Das et al., 1998; Gulati et al., 2009; Lavie et al., 2022; Swaminathan & Moorman, 2009), parametric tests often yield relatively short event windows, the most common of which are $[-1; 1]$, $[-1; 0]$, and $[0; 1]$, suggesting the number of days before and after the alliance event on day 0.

*Carhart modified Fama-French model.* The Fama-French model has become popular because of its ability to more accurately predict stock market changes (Fama & French, 1993). As modified by Carhart (1997), the four-factor model extends the previously discussed market model. It includes three additional factors to explain the abnormal returns as follows:

(5) $r_{it} = \alpha_i + \beta_i r_{mt} + s_i SMB_t + h_i HML_t + u_i UMD_t + \varepsilon_{it}$, where $SMB_t$ refers to differential returns to portfolios of small versus large capitalization firms, $HML_t$ indicates the differential

returns to portfolios with high versus low market-to-book ratio firms, and $UMD_t$ represents the differential returns to portfolios of firms with high versus low prior returns. As in the market model, abnormal stock returns are calculated by taking the difference between the estimates obtained from this model to predict the daily stock returns for each firm for the alliance announcement day and the actual returns.

Data on firm and market stock returns can be retrieved from CRSP. Data on the four factors are also available through Kenneth French's data library, which contains data on monthly returns from July 1963 and is constantly updated.[3]

**3.4.2. Long-term abnormal stock returns**

An event study methodology is often called an approach to calculate the immediate, short-term stock market reaction to a specific corporate event, primarily over a few days surrounding it. A long-horizon event study normally uses an event window of one year or more. While this allows estimating the effect of an alliance announcement over longer periods, the calculated effects can also be biased. Contrary to the analysis of short-term stock market reaction, there is a higher chance that more intervening firm-specific events can influence the estimates when the event window is substantially extended. The significance of long-run abnormal stock returns can be overstated due to cross-correlations between observations (Bernard, 1987; Kothari & Warner, 2007). In addition, the estimates of long-term abnormal returns may vary significantly depending on a model choice as the systematic bias due to imperfect expected returns is compounded over a longer period. Hence, scholars should be aware of these substantial issues of the event study methods to estimate long-term stock market reaction to corporate events.

[3] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

There are two estimation approaches to measure long-run abnormal stock returns: the buy-and-hold abnormal return (BHAR) method and the calendar time portfolio method. The key advantage of the BHAR method is that it captures the true magnitude of returns of a corporate event, while the main advantage of the calendar time portfolio method is that it allows controlling for cross-sectional dependence among sampled firms and is less sensitive to an asset pricing model that is poorly specified. At the same time, the disadvantage of the BHAR method is that it may produce inflated estimates due to compounding effects (Ang & Zhang, 2011), while the calendar-time portfolio approach is often criticized for being too conservative and having low power, i.e., the ability to detect abnormal returns when they are present (Kothari & Warner, 2007). In this study, we focus on the BHAR method as it is the most often used when estimating long-term abnormal stock returns to corporate events in marketing.

The BHAR approach considers the difference between the buy-and-hold returns of event firms and the characteristic-based matched portfolios (Barber & Lyon, 1997; Kothari & Warner, 1997). Mitchell and Stafford (2000, p. 296) define BHAR as “the average multiyear return from a strategy of investing in all firms that complete an event and selling at the end of a prespecified holding period versus a comparable strategy using otherwise similar nonevent firms.” Once a matching firm or portfolio is identified, BHAR calculation is straightforward. Formally, we can define a $T$-month BHAR as:

(6) $BHAR_{it} = \prod_{t=1}^{T}(1 + r_{it}) - \prod_{t=1}^{T}(1 + r_{bt})$, where $r_{it}$ is the month $t$ return of event firm $i$ and $r_{bt}$ is the month $t$ return of the benchmark portfolio or index $b$. For example, the benchmark returns for BHAR can be based on the CRSP indices or Fama-French portfolios.

### 3.5. Estimating the effect of alliance events on CAR and BHAR

Prior research utilized two modeling approaches to estimate the association between alliance announcements and firm CAR (BHAR). Traditionally, scholars relied on ordinary least squares (OLS) models. However, recent studies called for more advanced modeling techniques, such as hierarchical linear modeling or HLM (Koval, 2021; Thomaz & Swaminathan, 2015). HLM methodology has specific advantages over OLS when conducting event studies in B2B settings. HLM is more appropriate when (1) the data are nested, i.e., when firms announce multiple alliance events in the same calendar year; (2) the data are unbalanced, such that some firms repeatedly announce alliance events throughout the observation period, while others report only one alliance during the same period. HLM helps avoid bias in the estimation of standard errors. Suppose data are grouped, such as when a single firm forms several alliances, and the group effects are not taken into account in the regression model. In that case, the independence of the residuals assumption is violated, and the standard errors are underestimated (Snijders & Bosker, 2012). Like OLS, HLM allows a direct interpretation of the model's coefficients (Thomaz & Swaminathan, 2015).

In Stata, fitting a two-level HLM model (alliances are nested in firms) uses the *"mixed"* command. One can conduct a likelihood-ratio (L.R.) test comparing the two-level model with one-level ordinary linear regression to see whether such a model is appropriate. The output table after "mixed" contains the $\chi^2$ statistic and the p-value for this L.R. test—it is denoted as "L.R. test vs. linear model."

## 4. Application of event study in alliance research

### 4.1. Data, sample, and variables

We extract data on strategic alliance announcements from the SDC Platinum database (Joint Ventures & Strategic Alliances module) from 1990 to 2020. Prior to 1990, alliances have not been a frequent phenomenon (Hagedoorn, 2002; Lavie, 2007; Zaefarian et al., 2022). Because we use the event-study methodology to capture a firm's abnormal stock returns following an alliance announcement, our sample consists of publicly traded firms with accessible financial data on stock returns. We extract data on stock returns from the CRSP database. Since CRSP is a U.S. Stock and Index database, we further limit our analysis to abnormal stock returns of public firms headquartered in the U.S. In line with prior research, we do not include firms and alliances with a primary SIC code in the 6000s (depository institutions) and 9000s (non-classifiable establishments) since their returns may not be comparable with those of other industries (Misangyi, Elms, Greckhamer, & Lepine, 2006). Finally, because very small firms do not have consistent alliance coverage (Schilling, 2009) and their returns are more volatile and anomalous (Jegadeesh & Titman, 2001; McGahan & Porter, 1997), we exclude firms with total assets not exceeding $15 million.

Importantly, we need to include alliance- and firm-level characteristics in our models that have been claimed to affect abnormal stock returns from alliance announcements. Event studies in alliance research heavily emphasize the role of firm-level factors (e.g., firm size, R&D intensity, profitability, leverage, partnering experience) for value creation from an alliance (e.g., Gulati et al., 2009; Li & Reuer, 2022; Swaminathan & Moorman, 2009). Table 4 describes all independent variables that are included in the model. Data used to construct the included firm-level variables is obtained from COMPUSTAT and SDC Platinum. Alliance variables are derived from SDC Platinum. Our initial sample (i.e., before including firm-level variables) consisted of 27,828 firm-alliance observations. Because information on several firm-level variables is unavailable across all years, the final sample is reduced to 27,512 firm-alliance observations. There are ultimately 3,936 unique firms in the final sample. Table 5 shows the composition of firms and alliances by main activity.

-----Insert Tables 4 and 5 about here-----

### 4.2. Estimating cumulative abnormal stock returns

In line with alliance studies in the marketing field, we calculate firm abnormal returns using two approaches widely adopted by B2B scholars—the conventional market model (e.g., Swaminathan & Moorman, 2009) and the four-factor model (e.g., Fang et al., 2015; Oh et al., 2018). We use an estimation window of 240 days ending ten days before the event day, i.e., 250 to 10 trading days before the day of the alliance formation announcement. Following another standard practice, we exclude firms with concurrent alliances three days before and after the alliance announcement day to ensure the treatment of confounding effects (e.g., Das et al., 1998; Tipton, Bharadwaj, & Robertson, 2009).

We then proceed by selecting the appropriate event window. As mentioned earlier, event studies applied in alliance research typically adopt event windows around one day before and/or one day after the alliance formation announcement (e.g., Fang et al., 2015; Oh et al., 2018; Swaminathan & Moorman, 2009). This is because information about alliance announcements may leak in the press earlier, and it can take time to disseminate it over time (Sorescu et al., 2017). Due to sample specifics, the appropriate event window may vary, so it is often empirically determined. We calculate a t-statistic and Patell's (1976) z-statistic for the average CAR across different event windows and estimation techniques in the present study. The results are reported in Table 6. As seen from the table, the statistical power drops the more the event window extends beyond one day surrounding an alliance announcement. This tendency is inherent in both the market model and the four-factor model. The results do not straightforwardly point toward a specific window and model. For the $[-1; 0]$ event window, the average CAR points towards the market model while t-statistic and Patell z-statistic suggest the four-factor model. The highest Patell z-statistic is observed for the $[0; 1]$ event window, yet the average CAR and t-statistic are lower compared to $[-1; 0]$. Given that the average CAR is higher for the $[-1; 0]$ event window and the market model while the difference in t-statistic and Patell z-statistic is very low, we will use CAR produced by the $[-1; 0]$ event window and the market model for our subsequent analysis. In general, given that there is no significant difference in terms of average CAR and inferential statistics between the market model and the four-factor model, it may be preferred to use the former (Sorescu et al., 2017).

-----Insert Table 6 about here-----

**4.3. Analyzing factors that affect CAR and BHAR from an alliance announcement**

We estimate the effect of various alliance- and firm-specific characteristics on firm CAR following an alliance announcement. We then test whether a multilevel model is required. We first estimate a two-level HLM, where the first level in the model is the alliance, and the second level is firm. We then perform a likelihood-ratio test to see whether the two-level HLM model is more appropriate than a one-level linear model. The results of the test favor the use of the HLM model ($\chi^2 = 999.66, p < 0.01$). This is also demonstrated by an intraclass correlation coefficient of 0.36, which indicates that observation nesting is appropriate (Snijders & Bosker, 2012).

Table 7 presents the results of two HLM estimations (Models 1 and 2). Model 1 reports estimates of the direct effects of the alliance- and firm-level factors outlined in Table 4. Coefficients for technological alliance ($\beta = 0.004, p < 0.01$), alliance scope ($\beta = 0.002, p < 0.01$), firm size ($\beta = -0.003, p < 0.01$), firm profitability ($\beta = -0.013, p < 0.01$), and R&D intensity ($\beta = 0.015, p < 0.05$) are strongly significant. The coefficient for joint venture ($\beta = 0.002, p < 0.10$) is marginally significant. While several of these effects align with prior studies, the available empirical evidence remains mixed. It could be due to relatively dated samples (often, the period spans the 1990s through the early 2000s) and/or focus on specific industries.

-----Insert Table 7 about here-----

The observed statistically significant directionality of technological alliance and alliance scope conforms to the existing arguments in the alliance literature. Technological alliances generate higher abnormal returns by signaling investors a more significant cost advantage. Fixed costs incurred in an alliance should be lower than in an individual effort due to economies of scale, scope, and shared overheads (Das et al., 1998). Alliances with a greater functional scope should result in higher abnormal stock returns as they signal a more significant financial potential and can indicate a greater partner commitment (Kalaignanam, Shankar, & Varadarajan, 2007). Explaining the coefficient for joint venture may be less theoretically straightforward. Our results confirm the argument that an equity alliance can secure the partner's commitments and limit competitive tensions (Gulati, 1995), thus increasing the value of the alliance (Fang et al., 2016). However, a stream of research acknowledges that firms should, in theory, select an appropriate alliance structure that provides the required degree of protection to the involved parties (Kogut, 1988). Since the benefits match the costs, there should be no net financial and shareholder value gains (Houston & Johnson, 2000). There has also been little empirical work on contrasting abnormal returns for equity- and non-equity alliances, as the majority of event studies applied to alliance announcements have narrowed their analysis either to equity joint ventures (e.g., Gulati et al., 2009; Koh & Venkatraman, 1991) or non-equity alliances (e.g., Das et al., 1998; Swaminathan & Moorman, 2009). Limited empirical studies that contrast equity- and non-equity alliances, either directly or in a form of a control variable, do not find statistically significant difference in abnormal returns (e.g., Houston & Johnson, 2000; Lavie et al., 2022; Marciukaityte, Roskelley, & Wang, 2009), yet their data is often industry-specific and sometimes not recent.

The statistically significant coefficients for firm size, profitability, and R&D intensity in Table 7 align with specific theoretical arguments. One could resort to resource dependency theory in explaining the effects of firm size and profitability. Larger firms often search for smaller innovative counterparts to obtain their technological know-how, making the latter's relative bargaining power higher in a strategic alliance (Das et al., 1998). Unlike small firms, large firms may also create less value from an alliance due to limited reputation spillovers (Koh & Venkatraman, 1991). While research has confirmed this relationship, many studies have found no significant effect of firm size on abnormal returns (e.g., Anand & Khanna, 2000; Gulati et al., 2009). In some cases, the effect was positive (e.g., Amici, Fiordelisi, Masala, Ricci, & Sist, 2013). Similarly, the coefficient for firm profitability is negative and significant. This could be due to extra costs incurred from high-performing partners' "hold-up" problem (Das et al., 1998). Specifically, partners with higher profitability tend to make initial investments in equipment and personnel, while the other party costs remain minimal. The presence of the hold-up problem is internalized by the investors, thus lowering abnormal returns from an alliance announcement. As with firm size, the empirical evidence remains mixed: most of the studies tend to either find a negative effect (e.g., Das et al., 1998; Li & Reuer, 2022) or the absence of statistical significance (e.g., Piaskowska, Nadolska, & Barkema, 2019). The positive effect of R&D intensity can be explained using resource-based logic. R&D intensity is often associated with capabilities that help firms identify and assimilate external knowledge derived from strategic alliances, thus allowing firms to maximize shareholder value (e.g., Fang et al., 2016; Gulati et al., 2009).

It is worth noting that several other firm-level factors have been found significant in prior research yet are not significant in our sample. Firm financial resources captured by leverage may affect abnormal returns from an alliance by signaling the munificence of funds available for investing (Sadovnikova & Pujari, 2017). General partnering experience has been associated with relational capability that improves a firm's alliance management skills and increases the efficiency of collaboration, ultimately getting higher gains from alliances (Anand & Khanna, 2000; Kale, Dyer, & Singh, 2002). However, empirical evidence for the direct effect of such experience has been mixed (Liu & Ravichandran, 2015).

We further proceed to investigate possible contingencies to the direct effects. We perform exploratory analysis by regressing cumulative abnormal returns on the direct effects and all possible cross-level interactions. HLM offers a way to appropriately estimate cross-level interaction effects compared to a commonly used moderated multiple regression (Aguinis et al., 2013). Interactions not turning statistically significant after the initial HLM estimation have been eliminated, and the model has been re-estimated. We mean-center continuous variables and include all cross-level interaction effects as part of the same model. The estimates are reported in Model 2 of Table 7. Four interaction coefficients are significant: technological alliance × firm size ($\beta = 0.002, p < 0.01$), technological alliance × R&D intensity ($\beta = 0.022, p < 0.05$), alliance scope × leverage ($\beta = -0.009, p < 0.01$), and joint venture × firm size ($b = -0.001, p < 0.01$). The negative interaction between technological alliance and firm size is observed because large firms may become more vulnerable to opportunism in a technological rather than a non-technological (e.g., marketing or distribution) alliance. The positive interaction between technological alliance and firm R&D intensity may imply a superior capability of an R&D-intensive firm to handle product complexity and the high cost of product development inherent in technological alliances. Next, we observe a negative and significant coefficient for the interaction between alliance scope and firm leverage. Firms with substantial levels of financial leverage (the ratio of debt to assets) are often considered risky, having lower growth opportunities (Smith & Watts, 1992) and organizational efficiency (Guo, Legesse, Tang, & Wu, 2021). While engaging in alliances with a broader scope may signal investors more significant financial potential, the ability to realize this potential may be lower in firms with high leverage. Finally, the negative interaction between joint venture and firm size may exist because small firms in an equity alliance can secure more significant resource flows and commitments from their partners (Gulati, 1995). Large firms are expected to have even more significant resource commitment in equity alliances and could experience even greater reputation spillovers. As a result, small firms will have higher abnormal returns from alliance announcement in equity joint ventures versus non-equity alliances.

We adopt a marginal effects approach to develop a more nuanced interpretation of the interaction effects and further investigate the size and directionality of the relationship between alliance-level variables and abnormal stock return from an alliance formation announcement (Busenbark, Graffin, Campbell, & Lee, 2022). We calculate and plot the marginal effects (a one-unit change) of technological alliance, alliance scope, and joint venture at different values of firm-level moderators (i.e., firm size, R&D intensity, and leverage). The dots in Figures 1-4 thus represent the point estimates (with the 95% confidence intervals) of $\beta x$ at the specific values of the moderators ranging from the 1st to 99th percentile. In doing so, we also follow the recommendations of Aguinis et al. (2013) by framing our higher-level variables as moderating factors that affect the relationship between lower-level variables and abnormal returns. Interestingly, the plots demonstrate that the effects of technological alliance and joint venture turn negative under high values of firm size. Similarly, the relationship between alliance scope and abnormal returns is negative when financial leverage is high (approaches a value of 1, which is considered risky for a firm).

-----Insert Figures 1-4 about here-----

Finally, we estimate an HLM model to predict BHAR and compare the effects with CAR. As with CAR, the use of a two-level HLM model is justified, favored by the L.R. test ($\chi^2 = 2191.03, p < 0.01$) and an intraclass correlation coefficient of $0.34$. Because we have sufficient data points, we calculate the three-year post-announcement BHAR for the event firm. Prior research has noted that over half of strategic alliances terminate prematurely (e.g., Cui, 2013; Koval, 2021), with three years being a reasonable period to extract the most value from an alliance (Hashai, Kafouros, & Buckley, 2018; Penney & Combs, 2020). To calculate the long-run return of the benchmark portfolio, we use the equal-weighted approach with annual rebalance, as available in the WRDS Long Run Event Study tool Multilevel model is also appropriate. This approach may help better deal with potential abnormal changes in stock prices, especially when dealing with a series of unplanned events, yet there is a risk of overestimating BHAR (Barber & Lyon, 1997). In general, it is important to recall that long-horizon event studies face significant challenges due to systematic errors over time and sensitivity to model choice (Nguyen, 2023), and researchers should therefore use them with caution.

The HLM estimates for the model predicting BHAR are reported in Table 8. Except for the outcome, the set of independent variables remains the same as in Table 7 for comparability. In comparison with CAR (Table 7), the coefficients for alliance scope, joint venture, and firm profitability are not statistically significant in Model 1 of Table 8, while the coefficients for technological alliance, firm size, and R&D intensity are significant. In terms of interaction coefficients, only technological alliance × R&D intensity predicts BHAR positively and significantly in comparison with CAR. However, some direct effects are significant in the HLM estimation of BHAR as compared to CAR. These effects are number of alliance participants ($\beta = 0.059, p < 0.01$), leverage ($\beta = 0.515, p < 0.01$), and product diversification ($\beta = -0.166, p < 0.01$). The number of alliance participants is positively associated with BHAR because they may offer a larger pool of shared knowledge in an alliance, which helps effectively seize emerging opportunities (Beamish & Kachra, 2004). As mentioned earlier, leverage may create shareholder value from an alliance through the munificence of funds available for internalizing opportunities (Sadovnikova & Pujari, 2017). Higher product diversification may deplete managerial resources (Wan & Hoskisson, 2003), forcing firms to be less dedicated to each individual alliance, ultimately resulting in less shareholder value. In sum, scholars need to be aware that the estimations of CAR and BHAR may not yield the same results. While BHAR allows for compounding and longer lengths of the event window, long-horizon event study methods have a risk of being poorly specified and, hence, may produce biased results (Kothari & Warner, 2007).

## 5. Discussion and conclusion

Event studies have been essential to examine the shareholder value creation potential of B2B relationships, such as strategic alliances. Abnormal stock returns following an alliance announcement constitute a key metric to capture alliance success as they have been shown to highly correlate with a managerial assessment of alliance performance (Kale et al., 2002; Koh & Venkatraman, 1991; Liu & Ravichandran, 2015). The article's event study on a large sample of alliance announcements benefits B2B marketing scholars and practitioners in several ways.

We presented a systematic analysis of the value-creation potential of strategic alliances. Using an extensive sample covering strategic alliance announcements over the three recent decades (1990-2020), we investigated the effect of several important alliance- and firm-level characteristics on firm abnormal stock return following an alliance announcement. Our analysis indicated that technological alliances, joint ventures, broader alliance scope, and firm R&D intensity create shareholder value, while firm size and profitability have a negative effect. Consequently, we conducted an exploratory analysis of cross-level interactions (i.e., interactions of the firm- and alliance-level factors) that identify the conditions under which shareholder value is created or reduced. Specifically, we found that larger firms gain less value from announcing technological alliances than smaller firms, while firms with higher R&D intensity gain more value from such alliances. We also found that firms with lower financial leverage generate higher value from alliances with a larger scope. Finally, smaller firms gain more value from alliances organized as joint ventures than larger firms.

### 5.1. Theoretical and methodological implications

The results of our study make several important theoretical and methodological contributions. First, we extend the B2B relationship literature (e.g., Oh et al., 2018; Pasirayi, 2020; Truong et al., 2022) by conducting an overarching study on factors influencing firm value from an alliance announcement. In addition to short-term stock market reactions, we also look at the long-term effects of alliance formations that have been rarely examined in prior research. The merit of our analysis is to improve B2B scholars' understanding of the conditions under which strategic alliances are most promising in terms of value creation. Scholars could develop more specific research questions concerning forming such alliances.

Second, we build on and extend the methodological study of Ullah et al. (2021) to show how B2B scholars can apply the event study methodology in the strategic alliance context. Importantly, our analysis helps direct scholarly attention to various empirical issues in event studies conducted with alliance data, such as data availability and complexity of coding alliance variables, finding the appropriate event and estimation windows. In particular, data in alliance research is usually multilevel as it incorporates firm- and alliance-specific information. Scholars may therefore need to employ an appropriate modeling approach to estimate regression coefficients and standard errors correctly. We have pointed to hierarchical linear modeling—a regression technique that helps avoid bias in estimating standard errors and is particularly appropriate when studying cross-level interactions (Aguinis et al., 2013). Therefore, we recommend that scholars consider this modeling approach when conducting event studies to examine alliance-related events and discuss how one can test whether a multilevel modeling approach is needed. We also elaborate on different sources of strategic alliance data, including the news aggregators with raw alliance data. We discuss how to code alliance variables using the readily available information in the dedicated databases, such as SDC Platinum, or by studying the alliance announcements themselves. Concerning the choice of the appropriate event windows, we recommend the tests relying on a t-statistic and Patell's (1976) z-statistic. Importantly, we also extend the study of Ullah et al. (2021) by shedding light on the event study methodology to calculate not only the short-term but also the long-term value effects of firm alliance announcements.

In sum, our study helps raise scholarly awareness of working with alliance data and testing hypotheses where abnormal stock returns from an alliance formation act as a dependent variable. Our work enhances scholarly understanding of how to design event-study-based research in the context of strategic alliances and how to improve the validity and reliability of such findings.

**5.2. Managerial implications**

The results of our study also have important ramifications for managerial practice. Our results suggest that not all strategic alliance announcements create shareholder value for the firm—it depends on the alliance- and firm-specific characteristics. Specifically, the findings imply that managers should aim to publicly announce the formation of technological rather than marketing alliances, alliances organized as joint ventures rather than non-equity alliances, and alliances with a broader scope, as investors evaluate such events positively. To maximize value from alliances, firms need to have sufficient R&D intensity. However, larger and more profitable firms should be aware that announcing alliance formations may bring less value compared to their smaller and less profitable counterparts. Importantly, our findings show that technological alliances, firm size, and firm R&D intensity are the most important factors for managers to pay attention to, as their effects are consistently significant for both short- and long-term shareholder value creation.

Our results also point to the interplay of alliance- and firm-specific characteristics, with some combinations providing value-destroying (instead of value-creating) potential. Specifically, the results suggest that managers of smaller firms should consider announcing technological alliances, while larger firms should avoid such announcements as they are not rewarding for such firms. Managers of research-intensive firms should also consider announcing technological alliances as they have substantial positive value-creation consequences. Importantly, the findings suggest that managers of firms with higher financial leverage should be careful when announcing alliances performing multiple value chain activities, as such announcements may be detrimental to shareholder value. Managers of smaller firms should be interested in announcing an equity joint venture formation rather than a non-equity alliance to receive a positive investors' reaction, thus boosting shareholder value.

### 5.3. Limitations and future research directions

Our study could also be extended. We focus on the shareholder value created from alliance formation announcements. However, contrary to a large body of research on alliance formations, research on alliance terminations is limited (e.g., Cui, 2013). For example, Koval (2021) examines firm shareholder value due to alliance termination announcements employing the event study methodology to 196 unplanned alliance termination events during 1989-2008, where all alliance termination announcements are associated with the failure. Similar to prior research on alliances, Koval (2021) matches firms' stock return and financial data from CRSP and COMPUSTAT databases, respectively, with the strategic alliance data from the SDC Platinum database and business news. The study relies on the Carhart-modified Fama-French model to estimate abnormal stock returns. Due to the nested structure of alliance data (certain firms may announce multiple alliance terminations), Koval (2021) uses HLM to estimate the association between an alliance termination announcement and a firm's abnormal stock returns. The results show that firms with multiple alliances can gain shareholder value from alliance termination announcements under certain conditions. Such terminations allow the firms to reduce substantial alliance management costs. Future research needs to extend this line of inquiry to understand better the factors underlying shareholder value creation from alliance terminations and formations.

Event study methodology can also be applied when examining the shareholder value of various strategic marketing events, such as introducing new products or discontinuing existing ones, entering a new or re-entering the existing market through a local subsidiary or acquiring a local company, or exiting the market. Thus, it has applicability in multiple marketing research areas beyond B2B relationships. Future research could examine how the event study methodology should be appropriately applied when calculating both short-term and long-term shareholder value effects of such marketing events.

Finally, the event study methodology would be helpful when examining firm strategic events related to corporate social responsibility or irresponsibility. Sadovnikova and Pujari (2017) show that green partnerships generate short-term and long-term shareholder value effects. Future research could conduct events studies to look at events like green product introductions that should be positively evaluated by investors or more negative ones like collaboration with a socially irresponsible supplier and to which extent they can create or destroy firm shareholder value in the short and long run.

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Table 1. Overview of event study methodology applications in B2B literature

| **Study** | **B2B relationship** | **Short-term stock reaction** | **Long-term stock reaction** | **Key findings** |
|---|---|---|---|---|
| Das et al. (1998) | Marketing and technological alliances | Yes | No | Announcements of technological alliances generated greater abnormal stock returns than marketing alliance announcements; the abnormal stock returns were negatively associated with firm profitability and size. |
| Swaminathan and Moorman (2009) | Marketing alliances | Yes | Yes | Marketing alliance announcements create value for the participating firms; relational network characteristics and marketing alliance capability significantly moderate this relationship; no significant long-term effects. |
| Fang et al. (2015) | Alliances between upstream biotech firms and downstream pharmaceutical firms to co-develop new products | Yes | No | The alliance governance structure, partner technological capability, and the market's competitiveness influence the link between co-development timing and firms' abnormal stock returns. |
| Fang et al. (2016) | Marketing alliances | Yes | No | Plural governance structures outperform dyadic structures when marketing alliances perform product-related tasks, the partnering firm has more alliance experience, or the industry is fast-growing; dyadic governance structures outperform plural ones when the market is more competitive. |
| Cao and Yan (2017) | Brand alliances | Yes | No | A firm gains higher stock returns from alliances when its partner's brand value is higher; brand value differential reduces the positive effect of brand value; the partner's brand alliance experience increases the positive effect of the partner's brand value. |

Table 1. Overview of event study methodology applications in B2B literature (continued)

| Study | B2B relationship | Short-term stock reaction | Long-term stock reaction | Key findings |
|---|---|---|---|---|
| Sadovnikova and Pujari (2017) | Green partnerships | Yes | Yes | Announcements of green marketing partnerships have a positive effect on shareholder value; announcements of green technology partnerships produce a negative effect; green technology partnerships accrue positive returns over a longer-term (1 year) period; in high-polluting industries, firms with a history of positive environmental performance have lower gains from announcements of green partnerships. |
| Oh et al. (2018) | Marketing alliances | Yes | No | Partner's customer satisfaction offers larger value gains when the marketing alliance includes research and development activities; when product market relatedness is too high or low, the partner's customer satisfaction reduces value gains; partner's satisfied customers are more rewarding in a slowly growing market. |
| Pasirayi (2020) | Store-in-store agreements | Yes | No | Store-in-store agreements increase firm value; firm value increases when retailers form store-in-store agreements with partners that are dissimilar and have a congruent brand image. |
| Truong et al. (2022) | Technology licensing contracts | Yes | No | Greater monitoring (enforcement) emphasis increases (reduces) the licensees' value; greater concreteness reverses these effects; combined, monitoring emphasis, enforcement emphasis, and concreteness offer the greatest increase in the licensee's value. |

Table 2. Overview of alliance data sources

| Database name | Key advantages | Key disadvantages |
|---|---|---|
| SDC Platinum | • It systematically tracks coverage of alliance-related announcements since 1988 (Anand & Khanna, 2000).<br>• Collects information from multiple sources, including U.S. Securities and Exchange Commission (SEC) filings, trade publications, other firm reports, and business news.<br>• It has a user-friendly interface, intuitive data structure, and ability to extract all necessary data in one Excel file. | • It may contain occasional errors in coded information (e.g., incorrect alliance dates or industry codes) that may require verification with other data sources (Schilling, 2009). |
| Factiva (LexisNexis) | • It is the most comprehensive database in terms of alliance events' coverage.<br>• It contains information on negotiations, consequent alliance formations, and alliance terminations if announced. Rarely do firms also release intermediate news about alliance activity after its formation.<br>• It is often used to verify information provided by alliance databases like SDC Platinum or when one is interested in compiling a unique dataset containing more information than in more convenient databases. Not all alliance-related information ends up in alliance-dedicated databases (Lavie, 2007; Schilling, 2009). | • Contrary to SDC Platinum, searching for and extracting information on alliance announcements from Factiva is largely manual, not automated.<br>• Alliance information extracted from Factiva should be manually coded. |
| Cortellis Deals Intelligence | • It tracks strategic alliances in the biopharmaceutical industry.<br>• It provides comprehensive information on partnering firms involved, alliance type, location, the total projected value of an alliance, and detailed alliance financials such as milestone and upfront payments and equity. These variables are rarely available in alternative databases.<br>• Similar to SDC Platinum, it also allows conveniently extracting alliance information for its consequent analysis. | • Limited generalizability of their results as the database only covers one industry. |

Table 3. Operationalization of common alliance variables

| Variable name | Operationalization | Data source |
| --- | --- | --- |
| Alliance function | Alliances may perform research and development (R&D) (Hagedoorn, 2002), marketing (Swaminathan & Moorman, 2009), manufacturing (Cui, 2013; Lahiri & Narayanan, 2013), licensing (Mooi & Wuyts, 2021; Wuyts & Dutta, 2008), and distribution agreements (Chan, Kensinger, Keown, & Martin, 1997), among other functions.<br>Some scholars combine several functions to denote a broader nature of an alliance. For example, Das et al. (1998) distinguished between technological (R&D, licensing, and manufacturing) and marketing (distribution and sales) alliances. | In SDC Platinum, alliance functions are denoted with a dedicated column for each function. If a specific function is present, it is coded as "Yes" if it is present in the alliance or "No" if absent. In addition, there is a column called "Activity Description" listing all alliance functions. In other alliance-dedicated databases, alliance functions are coded in a similar manner. Usually, information on alliance functions is extracted from the announcement text. |
| Alliance scope | From prior alliance research (e.g., Cui, 2013; Kalaignanam et al., 2007), alliance scope is measured as the number of different functional areas in which the partners choose to cooperate. | Information is available in SDC Platinum in the columns corresponding to the alliance functions described above. This information comes from the alliance announcement text. |
| Number of alliance participants | Prior research distinguishes between dyadic alliances involving only two partnering firms and multipartner alliances comprising more than two partners (Fang et al., 2016; Lavie, Lechner, & Singh, 2007). | The number of alliance participants has already been coded in SDC Platinum, the "Number of Participants in Alliance" column. When using a different data source without a dedicated column, one can count the number of alliance parties mentioned in the correspondent alliance announcement. |
| Alliance organizational form | Alliances can be formed as contractual B2B agreements, i.e., without any equity involvement. They can also be formed as equity joint ventures—separate organizations with partnering firms' real and financial assets and a board of directors with partners' representatives (Kogut, 1988; Sampson, 2007). | In SDC Platinum, one can find information on whether the alliance was formed as an equity joint venture by looking at the "Joint Venture Flag" column: equity joint ventures are coded as "Yes" and contractual agreements as "No." In the former case, the database additionally provides information on each partner's correspondent stake in the alliance. In other databases or when using business news services, one can find this information in the alliance announcement text. While a joint venture form is normally stated explicitly, contractual arrangements can be mentioned as "agreements" or "strategic alliances." |

Table 3. Operationalization of common alliance variables (continued)

| Variable name | Operationalization | Data source |
|---|---|---|
| Cross-border alliance | Captures whether an alliance performs activities in a geographic location other than a focal firm's domestic location. | In SDC Platinum, the "Cross Border Alliance" column indicates that alliances include activities in more than one country (labeled as "Y"). In the database, a certain percentage of alliances are also marked as "Supranational," meaning they may operate in multiple world regions. Researchers may find it not straightforward to code such alliances' locations, and additional examination of the alliance announcement text may be needed. If no such information is provided, one possibility could be to code that such alliances operate in all major world regions. |
| Cross-border alliance partners | Captures whether alliance partners are located in different countries. | If this is the case, the "Cross Border Participants" column will be coded as "Y" and "N" for same-nation partners. It is worth noting that the SDC platinum database also distinguishes between the countries of corporate headquarters. This information can be found in the "Ultimate Participant Parent Country" column. |
| Alliance industry | Alliances may be formed in low-tech or high-tech industries, though most alliances will still belong to the high-tech sectors. One should consider the correspondent Standard Industrial Classification (SIC) codes of alliances to code alliance industry (Schilling, 2009). | Alliance industry information is conveniently coded in alliance databases like SDC Platinum, and the correspondent Standard Industrial Classification (SIC) codes are provided. SDC Platinum also provides information on the core code of the alliance's industry, which is often used. In news databases like Factiva, identifying the industry of an alliance can be more challenging. It could be done by looking at the alliance goal or often product developed in the alliance and trying to find the correspondent industrial sector. This process may not be straightforward and time-consuming. |
| Focal firm industry | Similarly, one should consider the correspondent Standard Industrial Classification (SIC) codes of alliances to code firm industry. | Similarly to the alliance industry, the SDC Platinum database conveniently reports the focal firm's SIC industry code. If such information is absent in the database, the researcher can find it by looking at complementary databases like COMPUSTAT. |

Table 4. Independent variables used to explain CAR

| Variable | Operationalization | Source |
|---|---|---|
| *Alliance level* | | |
| Technological alliance | Equals 1 if the alliance has an R&D function ("Yes" in "R&D agreement flag"), a licensing function ("Yes" in "Licensing agreement flag"), and/or a manufacturing function ("Yes" in "Manufacturing agreement flag") and 0 otherwise. | SDC Platinum |
| Alliance scope | The number of alliance activities in the "Activity description" field. | SDC Platinum |
| Joint venture | Equals 1 if the alliance is formed as an equity joint venture ("Yes" in "Joint venture flag") and 0 otherwise. | SDC Platinum |
| Number of alliance participants | The number of firms involved in the alliance. In SDC, this can be found in the "Number of participants in alliance" field. | SDC Platinum |
| Cross-border alliance | Equals 1 if the alliance activities span more than one country ("Y" in "Cross-border alliance flag") and 0 otherwise. | SDC Platinum |
| Cross-border participants | Equals 1 if the alliance includes partners from more than one country ("Y" in "Cross-border participants flag") and 0 otherwise. | SDC Platinum |
| Alliance industry | Dummy variables signifying the primary industry affiliation (a 2-digit SIC code) of the alliance. | SDC Platinum |
| Year of formation | Dummy variables signifying the year of alliance formation. | SDC Platinum |
| *Focal firm level* | | |
| Firm size | The natural logarithm of the firm's total assets (inflation-adjusted) in the year preceding the year of alliance formation. | Compustat |
| Profitability | The ratio of net income/loss to total assets in the year preceding the year of alliance formation. | Compustat |
| R&D intensity | The ratio of the firm's R&D expenditures to its revenues in the year preceding the year of alliance formation. | Compustat |
| Leverage | The ratio of long-term debt to total assets in the year preceding the year of alliance formation. | Compustat |
| Product diversification | $1-\sum s_j^2$ , where $s_j^2$ is a proportion of the firm's revenues derived from product segment $j$. | Compustat |
| Partnering experience | The natural logarithm of the accumulated number of all prior alliances in which the firm participated in the year preceding the year of alliance formation. | SDC Platinum |
| Firm industry | Dummy variables signifying the primary industry affiliation (a 2-digit SIC code) of the firm. | SDC Platinum |

Table 5. Composition of the final sample by the main industry activity of firms and alliances (top 10 industries)

| **Main industry activity of firms** | **% in sample** |
|---|---|
| Computer programming, data processing, and other computer-related services | 17.58 |
| Drugs | 8.46 |
| Electronic components and accessories | 5.23 |
| Surgical, medical, and dental instruments and supplies | 4.27 |
| Computer and office equipment | 3.71 |
| Communications equipment | 2.72 |
| Crude petroleum and natural gas | 2.36 |
| Laboratory apparatus and analytical, optical, measuring, and controlling instruments | 2.24 |
| Telephone communications | 2.11 |
| Research, development, and testing services | 2.03 |
| Other | 49.29 |
| **Main industry activity of alliances** | **% in sample** |
| Computer programming, data processing, and other computer-related services | 28.97 |
| Management and public relations services | 6.51 |
| Research, development, and testing services | 5.03 |
| Professional and commercial equipment and supplies | 4.29 |
| Drugs | 3.29 |
| Electronic components and accessories | 3.19 |
| Telephone communications | 2.68 |
| Communications equipment | 2.38 |
| Computer and office equipment | 2.29 |
| Miscellaneous durable goods | 2.23 |
| Other | 39.14 |

Table 6. Parametric tests for CAR across various event windows

| Event window | Market model | | | Four-factor model | | |
|---|---|---|---|---|---|---|
| | Average CAR | t-statistic | Patell z-statistic | Average CAR | t-statistic | Patell z-statistic |
| [-3; 3] | 0.0071 | 11.66 | 9.77 | 0.0067 | 11.15 | 9.20 |
| [-2; 2] | 0.0074 | 13.49 | 12.87 | 0.0072 | 13.30 | 12.46 |
| [-2; 1] | 0.0075 | 14.70 | 14.41 | 0.0074 | 14.64 | 14.28 |
| [-1; 2] | 0.0067 | 13.25 | 13.87 | 0.0066 | 13.21 | 13.57 |
| [-1; 1] | 0.0069 | 14.66 | 16.03 | 0.0068 | 14.78 | 16.07 |
| [-1; 0] | 0.0062 | 14.99 | 16.82 | 0.0061 | 15.09 | 16.88 |
| [0; 1] | 0.0059 | 14.00 | 16.89 | 0.0059 | 14.18 | 17.07 |
| N = 27,828 | | | | | | |

Table 7. HLM model estimates for CAR

| | Cumulative abnormal return (CAR) | |
|---|---|---|
| | (1) | (2) |
| Intercept | 0.002 (0.013) | 0.000 (0.013) |
| *Alliance level* | | |
| Technological alliance | $0.004^{***}$ (0.001) | $0.004^{***}$ (0.001) |
| Alliance scope | $0.002^{***}$ (0.001) | $0.001^{**}$ (0.001) |
| Joint venture | $0.002^{*}$ (0.001) | $0.003^{**}$ (0.001) |
| Number of alliance participants | -0.000 (0.000) | 0.000 (0.000) |
| Cross-border alliance | 0.001 (0.002) | 0.001 (0.002) |
| Cross-border participants | 0.001 (0.001) | 0.001 (0.001) |
| *Firm level* | | |
| Firm size | $-0.003^{***}$ (0.001) | $-0.003^{***}$ (0.001) |
| Profitability | $-0.013^{***}$ (0.003) | $-0.014^{***}$ (0.003) |
| R&D intensity | $0.015^{**}$ (0.007) | 0.001 (0.009) |
| Leverage | -0.002 (0.003) | -0.002 (0.003) |
| Product diversification | -0.001 (0.002) | -0.001 (0.002) |
| Partnering experience | 0.000 (0.001) | -0.000 (0.001) |
| *Cross-level interactions* | | |
| Technological alliance × Firm size | | $-0.002^{***}$ (0.000) |
| Technological alliance × R&D intensity | | $0.022^{**}$ (0.009) |
| Alliance scope × Leverage | | $-0.009^{***}$ (0.003) |
| Joint venture × Firm size | | $-0.001^{***}$ (0.000) |
| *Random-effects parameters* | | |
| Firm | $0.002^{***}$ (0.000) | $0.002^{***}$ (0.000) |
| Alliance | $0.004^{***}$ (0.000) | $0.004^{***}$ (0.000) |
| Observations | 27,512 | 27,512 |
| Log-likelihood | 35240.281 | 35269.443 |
| Overall model fit, $\chi^2$ | $320.538^{***}$ | $380.082^{***}$ |
| L.R. test vs. linear model, $\chi^2$ | $999.660^{***}$ | $991.660^{***}$ |
| Akaike information criterion | -70160.561 | -70210.886 |
| Bayesian information criterion | -68844.981 | -68862.416 |

$^{*}$ *$p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.*

Two-tailed p-values. Standard errors in parentheses. Alliance industry, firm industry, and year of formation dummies are included but not reported.

Table 8. HLM model estimates for BHAR

| | Buy-and-hold abnormal return (BHAR) | |
|---|---|---|
| | (1) | (2) |
| Intercept | -0.441 (0.352) | -0.413 (0.353) |
| *Alliance level* | | |
| Technological alliance | $0.090^{**}$ (0.036) | $0.085^{**}$ (0.036) |
| Alliance scope | 0.016 (0.018) | 0.014 (0.018) |
| Joint venture | -0.035 (0.035) | -0.045 (0.036) |
| Number of alliance participants | $0.059^{***}$ (0.013) | $0.059^{***}$ (0.013) |
| Cross-border alliance | 0.060 (0.055) | 0.060 (0.055) |
| Cross-border participants | -0.044 (0.027) | -0.043 (0.027) |
| *Firm level* | | |
| Firm size | $-0.109^{***}$ (0.016) | $-0.112^{***}$ (0.017) |
| Profitability | 0.053 (0.092) | 0.047 (0.092) |
| R&D intensity | $0.902^{***}$ (0.218) | $0.520^{*}$ (0.277) |
| Leverage | $0.515^{***}$ (0.121) | $0.509^{***}$ (0.121) |
| Product diversification | $-0.166^{**}$ (0.070) | $-0.166^{**}$ (0.070) |
| Partnering experience | 0.000 (0.021) | -0.000 (0.021) |
| *Cross-level interactions* | | |
| Technological alliance × Firm size | | -0.003 (0.013) |
| Technological alliance × R&D intensity | | $0.606^{**}$ (0.292) |
| Alliance scope × Leverage | | -0.051 (0.108) |
| Joint venture × Firm size | | 0.019 (0.014) |
| *Random-effects parameters* | | |
| Firm | $1.162^{***}$ (0.057) | $1.165^{***}$ (0.057) |
| Alliance | $2.289^{***}$ (0.027) | $2.287^{***}$ (0.027) |
| Observations | 17,258 | 17,258 |
| Log-likelihood | -33082.963 | -33079.169 |
| Overall model fit, $\chi^2$ | $790.405^{***}$ | $798.766^{***}$ |
| L.R. test vs. linear model, $\chi^2$ | $2191.030^{***}$ | $2198.270^{***}$ |
| Akaike information criterion | 66485.925 | 66486.337 |
| Bayesian information criterion | 67726.890 | 67758.326 |

$^{*}$ *$p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.*

Two-tailed p-values. Standard errors in parentheses. Alliance industry, firm industry, and year of formation dummies are included but not reported.

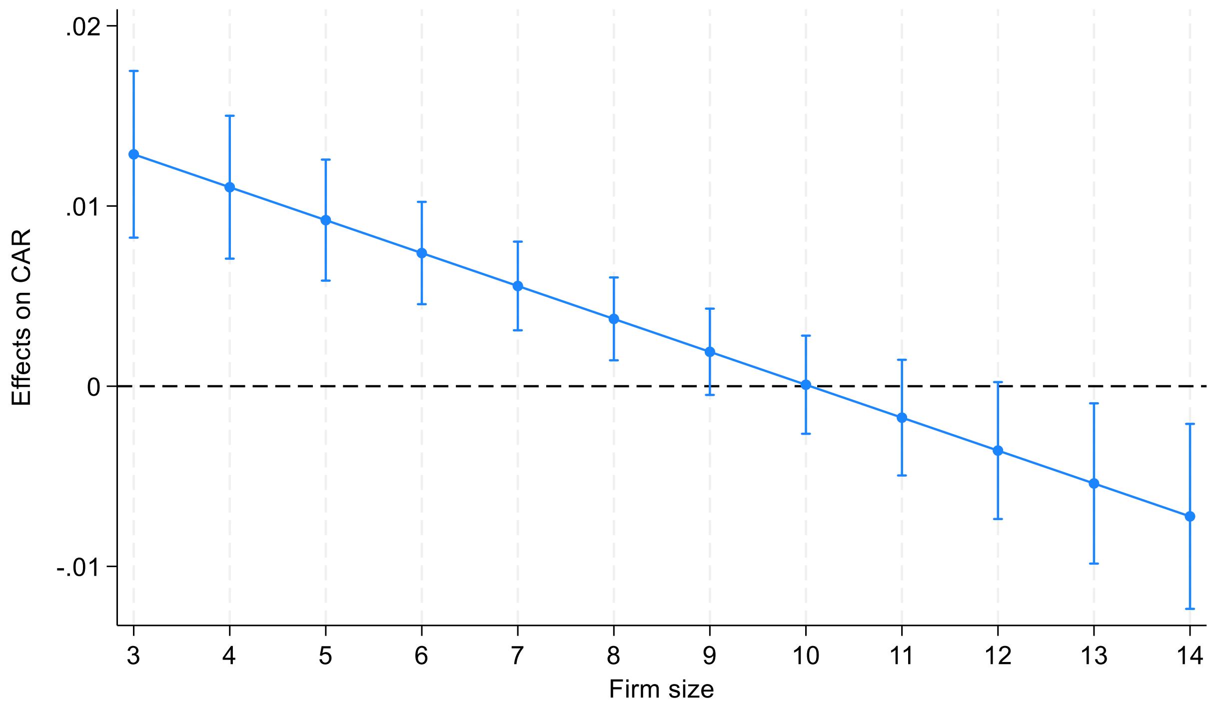


Figure 1. Change in marginal effects of *technological alliance* on CAR for different value of *firm size*

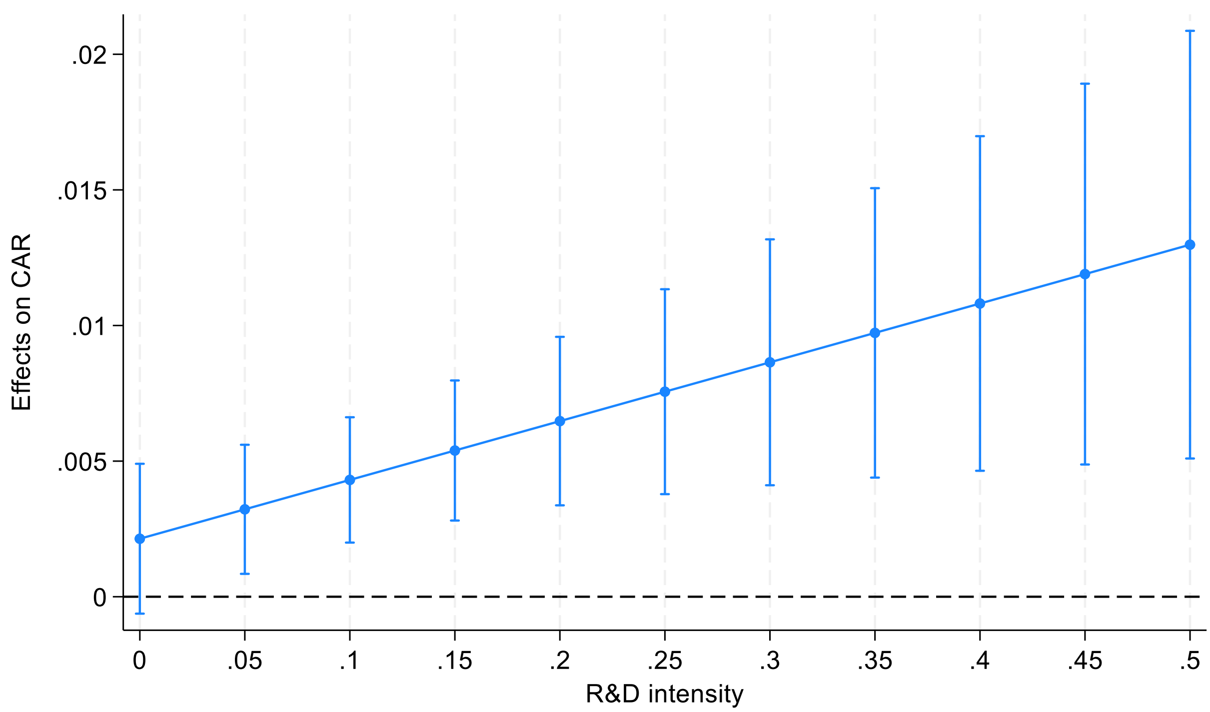


Figure 2. Change in marginal effects of *technological alliance* on CAR for the values of *R&D intensity*

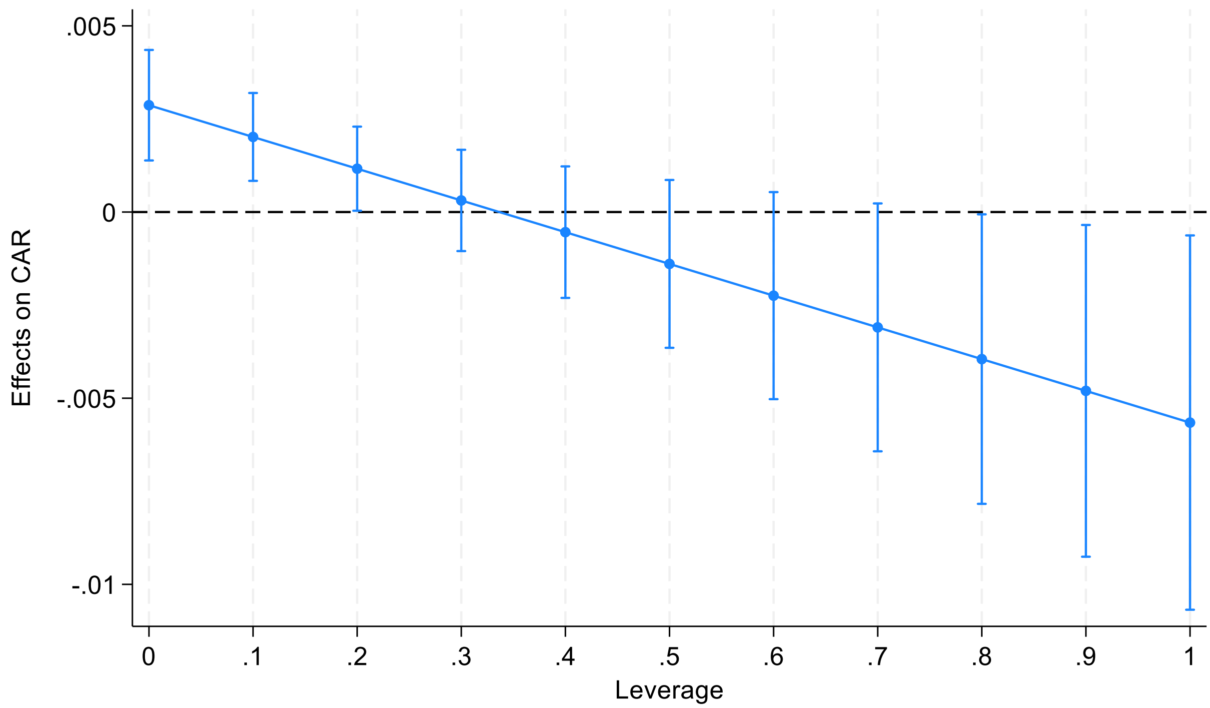


Figure 3. Change in marginal effects of *alliance scope* on CAR for different values of *leverage*

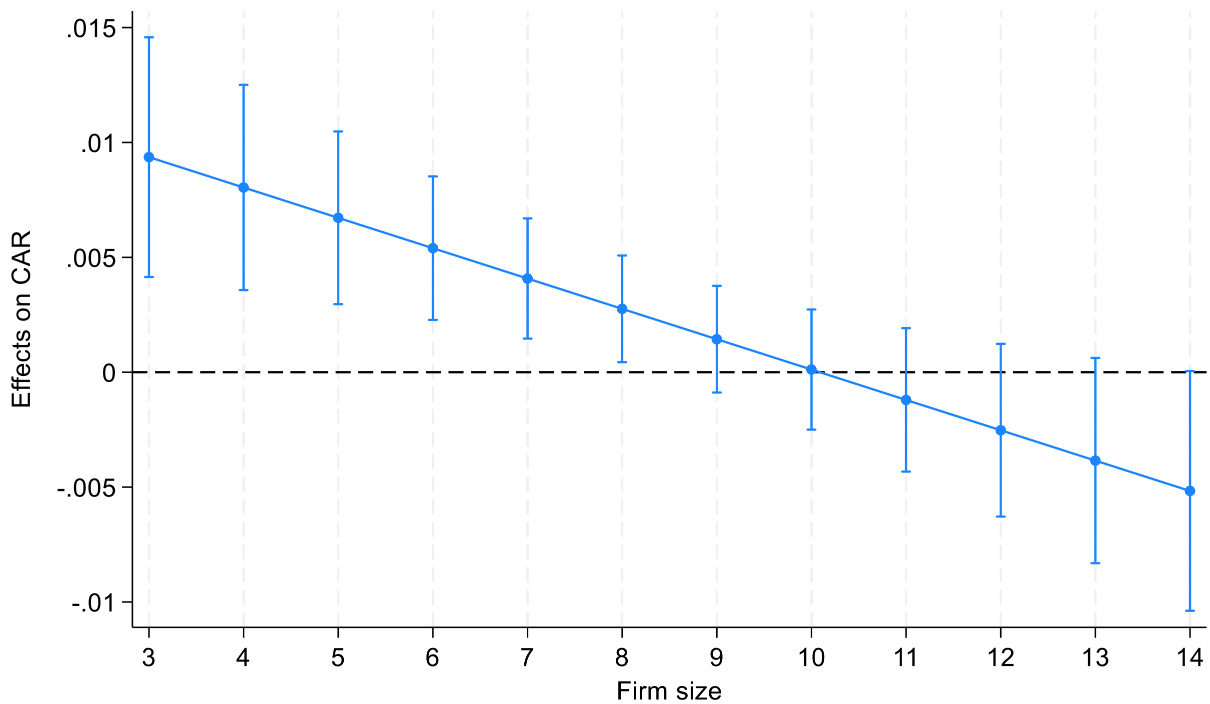


Figure 4. Change in marginal effects of *joint venture* on CAR for different levels of *firm size*