High-Tech Acquisitions by Low-Tech Firms: Does Acquirer Experience Count?

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We study whether experience matters for acquirers in nontech sectors when conducting acquisitions of high-tech targets. The topic is motivated by the rapid development of advanced and digital technologies that have fueled tech-related M&A volumes, where companies seek high-tech targets to substitute or complement their own R&D and to stay competitive. Studying 1146 tech-oriented deals announced by European acquirers during the period of 2006-2019, we find acquirer investors to be clearly optimistic about such takeovers with positive and significant two-day cumulative abnormal returns of 0.82%. We also find that industrial acquirers seem to gain substantially. Finally, one-time buyers were found to experience significantly higher cumulative abnormal returns than frequent buyers, and frequent buyers exhibited a weak declining return pattern in subsequent deals. This implies that companies are rewarded for acquiring digital technology, especially in their first initiative to digitalize their business.

Keywords:
High-tech, M&As, Experience

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1. Introduction

The digital revolution has advanced technological solutions in various fields, and digital technology brings important competitive capabilities to firms in all sectors. The role of digital technology is developing from enabling and supporting to influencing and even guiding the overall strategic direction of corporations (Ivang et al., 2009; Porter & Heppelmann, 2014). In addition, the recent economic boom has fueled firms' desire to grow, and Mergermarket (2018) reports a steadily rising number of M&A deals for approximately a decade now. The share of transactions involving a high-tech target has been growing faster than the overall M&A market, and the growth is increasingly characterized by firms operating in nontechnological sectors buying high-tech companies.[1] However, technology acquisitions are often seen as costly and challenging to acquirers. High-technology targets are typically characterized by high valuation multiples, and it is far from an easy task to integrate an innovative high-tech target into a large, traditional company. Nevertheless, some empirical studies, e.g., Kohers & Kohers (2000) and Lusyana & Sherif (2016), find that the market tends to exhibit excess enthusiasm about the potential benefits of many high-tech acquisitions and that this optimism has increased over time.

Several studies report evidence on the importance of general acquisition experience, or target familiarity in some form, either for acquisition probability (Duarte and García-Canal, 2004; Collins et al., 2009), performance/value creation in M&As (Beckman and Haunschild, 2002; Haleblian and Finkelstein, 1999; Porrini, 2004; Benou and Madura, 2005; Meschi and Metais, 2006; Yoon & Lee, 2016; Castellaneta and Conti, 2017) or the form of the acquisition, such as a full or a partial acquisition (Elango et al., 2013). Our study focuses on whether experience matters for acquirers in nontech sectors when conducting acquisitions of high-tech targets. First, in line with the results from most prior studies on the role of experience in M&As, acquirers more familiar with technology acquisitions could be expected to make more profitable deals through target selection or merger implementation. We call this the *experience gain* hypothesis. Second, a learning curve effect might support the idea that the first-tech transaction brings the largest benefits for a nontech firm. We call this the *declining benefits* hypothesis. We contribute to the prior literature in which technological acquisitions have rarely been analyzed specifically from the perspective of nontechnological acquirers – at most, these acquirers have been included as a separate subsample in some studies (Kohers & Kohers, 2000; Kallunki et al., 2009).

Studying 1146 tech-oriented deals announced by European acquirers during the period of 2006-2019, we find positive and significant two-day cumulative abnormal returns for the acquirers. In particular, industrial acquirers seem to gain substantially. Contrary to typical studies on the role of experience in M&As, we find that one-time buyers obtain significantly higher cumulative abnormal returns than frequent buyers, and frequent buyers exhibit a weak declining return pattern in subsequent deals.[2] Our results are therefore in line with the *declined benefits* hypothesis rather than the more classical view that suggests benefits from the experience. We contribute to prior literature by being the first to test the effects of tech acquisition experience on market reactions from acquiring high-tech targets.

[1] According to BCG (2017), technology deals accounted for approximately 30% of the total value of completed M&A transactions in 2016, of which approximately 70% involved a buyer from outside the technology sector.

[2] Our results are in line with the only prior study on the topic that we have found, the report by Boston Consulting Group (2017). The report concluded that the market has, counterintuitively, rewarded one-time technology acquirers instead of frequent acquirers. Nevertheless, over the medium term, frequent acquirers have performed better compared to the market.

The remainder of the paper is structured as follows. In section 2, we review prior literature and present our hypotheses. In section 3, the data and methodology are presented. Section 4 presents our results, and section 5 concludes the paper.

2. Literature review and hypothesis development

Motivations for mergers into the high-tech sector may, for example, be cost synergies, as outdated or manual processes are being replaced by newer solutions such as artificial intelligence and robotics (Arnold, 2002; Berk & DeMarzo, 2014); or a strategic motive, as it may be less costly to integrate acquired technology than to develop the same know-how or technology in-house (Higgins & Rodriguez, 2006; Arnold, 2002). Mergers involving high-tech can be either vertical, horizontal or even concentric mergers, where the takeover target could bring added value into the acquirer's product lines, market participation, or technologies (Cartwright and Cooper, 1992).

Generally, in studies of acquisitions, acquirer returns to acquisition announcements are often found to be insignificantly different from zero as competition for the target may increase prices so that the target gains most of the merger benefits and because of potential acquirer overconfidence (Roll, 1986). Especially in the case of high-tech acquisitions, such hubris has been found to play a role in decision making (Kohers & Kohers, 2001). Valuation in the high-tech sector is also regarded as more subjective due to a lack of historical financials and because a great proportion of the targets are privately held, making the hubris hypothesis highly relevant for the field (Kohers & Kohers, 2001; Rau & Vermaelen, 1998). It is hard to form expectations of how such potential hubris might influence our results as it may both lead to acquirers paying too much (in which case the announcement return on an e cient market would be poorer) or the market suffering from hubris, in which case announcement returns would exhibit excess optimism.

Overall, our study is linked to papers studying whether the announcement returns to acquirers are dependent on some form of prior acquirer experience. Prior studies have found some form of experience to matter for premiums paid, acquisition likelihood, or form. Beckman and Haunschild (2002) studied premiums paid on targets by acquirers. They found no significance for learning in the form of the number of prior acquisitions, but they report that firms in networks with heterogeneous partner experience pay lower premiums than those in networks with homogeneous partner experience. Collins et al. (2009) study M&As among the S&P 500 and find that firms' prior domestic and international acquisitions influence the likelihood of acquisitions in foreign markets by U.S.-based firms. In a study of Spanish firms, Duante et al. (2004) also find support for a positive link between acquisition experience and future acquisition probability. Studying cross-border high-tech acquisitions undertaken by firms from 36 countries, Elango et al. (2013) find that prior experience increases the likelihood of choosing a full rather than partial acquisition.

Studies of the relationship between experience and acquisition performance typically study the announcement return for the acquirer. Kohers and Kohers (2001) report that acquirers familiar with emerging technologies enjoy stronger investor confidence in high-tech takeovers. Drawing from learning theory in psychology, Haleblian and Finkelstein (1999) found support for a U-shaped relationship between organizational acquisition experience and abnormal announcement day returns for the acquirer using U.S. data. Porrini (2004) studied the effects of alliance and acquisition experience on high-tech and low-tech acquirers' announcement returns and found somewhat different results for the two groups. For high-tech acquirers, the results indicate a significant positive effect for alliance experience (but not for acquisition experience); and when linearity was studied, support for a U-shaped relationship for alliance experience was obtained. However, Meschi and Metais (2006) studied acquirer announcement returns for French acquisitions into the U.S. and found support for the opposite, i.e., an inverted U-shaped relationship. Studying U.S. acquirers of high-tech targets, Benou and Madura (2005) found that bidder shareholders are generally more optimistic when an experienced acquirer is involved. Kallunki et al. (2009) studied technology mergers by low- and high-tech firms and reported that the acquirer's stock price response to R&D investments increased substantially but only for technology acquirers. These acquirers also show stronger future post takeover profitability.[3] Their results indicate that nontech acquirers may lack some capabilities to successfully utilize the acquired technology and potentially be more subject to managerial hubris. Finally, a different performance measure (Internal Rate of Return, IRR) was studied by Castellaneta and Conti (2017) who investigated the relationship between experience (prior completed buyouts) and acquisition performance in U.S. private equity buyouts around a change in the regulatory environment. They report significantly positive relationships for experience but a significant negative effect for experience when interacting with transparency. They conclude that the positive IIRs seem to come more from target selection ability (when information is less transparent) than from restructuring ability as the more experienced firms perform worse when the information environment becomes more transparent.

In line with typical findings from prior research, we formulate an *experience benefit* hypothesis where we expect that for low-tech firms, prior experience (number of past transactions) positively influences acquisition performance (announcement returns for the acquirer). Behind the positive reaction can either be expectations of better target selection, better restructuring ability, or both.[4] When experience is accumulating, one might expect an increasingly positive effect from stronger experience, which is in line with the positive part of the U-shaped relationship found in several studies.

Hypothesis 1: There is a positive relationship between announcement returns for the acquirer and the acquirer's past experience from high-tech acquisitions.

Hypothesis 2a: The positive relationship between announcement returns for the acquirer and the acquirer's past experience is linear, i.e., stronger experience is associated with more positive returns.

However, prior literature is not completely uniform regarding the theory or empirical returns around past experience, especially concerning the accumulated experience. Both U-shaped and inversely U-shaped relationships have been found. Moreover, Aktas et al. (2009) and Al Rahahleh & Wei (2010) discuss the relevance of the hubris hypothesis for the case of frequent acquirers. The hypothesis suggests managerial overconfidence to be reinforced after an initial

[3] In contrast, Kohers and Kohers (2001) report no significant difference between the long-term performance of bidders from outside or inside the technology sector.

[4] A study reporting results contrary to the *experience benefit* hypothesis is the BCG (2017) study. They find that the market rewards first time tech acquirers more than experienced dealmakers. They suggest that this short-term price reaction may be due to the market interpreting the tech acquisition as a sign of the company understanding the need to transform, due to them finding a "once-in-a-lifetime opportunity", or due to a shift of the business model towards more innovative products or services. However, BCG (2017) also finds that the long-run (1 yr) performance is better (as compared to a market index) in the group of serial acquirers, suggesting that experience counts in the longer run for total performance.

successful deal, leading to a declining value-creation pattern in subsequent deals of serial acquirers. Apart from the hubris hypothesis, other typical explanations for the declining pattern have been suggested – for example, a diminishing number of valuable targets or increasing manager aggressiveness to acquire as they learn to identify synergies more e ciently (Klasa & Stegemoller, 2007; Aktas et al., 2009). Additionally, the learning curve effect as applied to production (see, e.g., Argote and Epple, 1990) suggests reduced rather than linear (or exponential) benefits after the implementation stages of new technology. We thus form an alternative *declining benefits* hypothesis as follows:

Hypothesis 2b: The positive relationship between announcement returns on the acquirer and the acquirer's past experience declines as experience accumulates.

3. Data and method

3.1 Data

This paper is focused on acquiring firms and their announcement returns in the case of high-tech acquisitions. All data is retrieved from the FactSet database. We require that the acquirer is a publicly listed nontech firm and that the target is a high-tech firm that is not necessarily listed. FactSet divides all acquisition transactions into the categories *financial buyer* or *strategic buyer* based on whether the acquisition was made for investment purposes or strategic business purposes. Only transactions involving an acquirer classified as a *strategic buyer* are included in our study.

Our sample selection process includes several steps. In step one, we restrict our selection to transactions involving *tech targets* classified as firms within one of the two-digit Standard Industrial Classification (SIC) codes defined in Kallunki et al. (2009) as the most technology-intensive industries.[5] Likewise, in step one, the sample was restricted to *nontech acquirers* defined as firms with any sector classification other than the two-digit SIC codes previously defined. Next, in step two, to identify high-tech and digitalization-oriented transactions from the sample even more accurately, the target companies' business descriptions were screened for 24 relevant high-tech keywords (see Appendix A1). This is a screening similar to that in BCG (2017). Our final sample includes, besides the transactions identified in the screening test, all remaining targets with "technology services", "electronic technology" or "health technology" as their primary FactSet sector. This was done in order to avoid putting too much emphasis on the keywords and accidentally excluding deals driven by less well-known technologies. The five largest target firm industries (primary FactSet industry) in the final sample were miscellaneous commercial services, packaged software, internet software/services, information technology services and industrial machinery. The classifications of the obtained sample were also well

[5] The optimal two-digit SIC codes for high-tech firms used by Kallunki et al. (2009) are the following: [28] chemicals and allied products; [36] electronic and other electrical equipment and components, except computer equipment; [35] industrial and commercial machinery and computer equipment; [37] transportation equipment; [38] measuring, analyzing, and controlling instruments; photographic, medical and optical goods; watches and clocks; [48] communications; [73] business services; and [87] engineering, accounting, research, management, and related services.

in line with a slightly more conservative high-tech classification by Kile and Phillips (2009).[6]

Geographical restrictions were also included. Recent digitalization reports, including PwC & 'Strategy&' (2018), find that Europe lags behind in digital transformation in regard to building ecosystems in customer solutions, operations, technology and people – particularly when compared to Asia-Pacific, which has clearly stronger levels of digital maturity. Fortunately, several Central European (e.g., Belgium, Germany, and the Netherlands) and Nordic countries are constantly strengthening their digital capabilities with companies already having digitalized more than 25% of their systems (Financial Times, 2018). To further examine the emerging technological adaptation in Europe, the acquirers were restricted to European acquirer companies (the country distribution is displayed in Appendix A2). For targets, no geographical restrictions were applied as the technology trend is strongly global – this would only limit the number of interesting transactions, especially as countries in the Americas and APAC are dominating in the supply of new, cutting-edge technology.

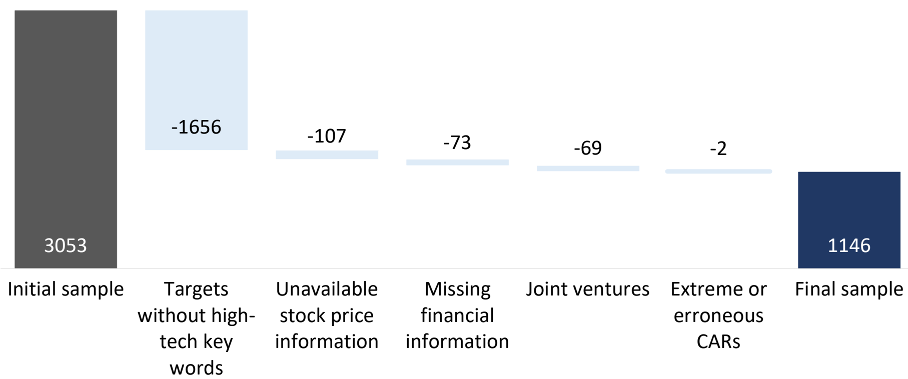
Regarding the *time frame* for the research, it was crucial to prioritize as recent data as possible. The decision was based on the newness of the digitalization-oriented M&A trend. For example, transactions made before the dot-com bubble would not have been fully comparable to these newer, technology-motivated takeovers. As technology is changing at a fast pace, the motivations to buy different technologies may differ from those present earlier, such as in Kallunki et al. (2009) with the study period ending in 2006. As previous research on high-tech takeovers lacks coverage of the most recent decade, the chosen time frame also forms an important part of the contribution of our paper. Accordingly, the period of January 1, 2006, to March 31, 2019, was chosen.

Other restrictions relevant to the study relate to transaction characteristics. First, a minimum deal size of €1 million was set to exclude the smallest transactions with indistinguishable public coverage. A higher minimum deal size would not have been optimal as the strong enthusiasm about high-tech deals may specifically arise from small and young startup acquisitions (Lusyana & Sherif, 2016). To prevent any problems arising from the small minimum deal size, a relative transaction size variable was included in the regression models. Second, in a similar manner to previous research, both pending and completed deals were included in the sample since only short-term reactions were studied. Finally, joint ventures and spinoffs were excluded similarly to BCG (2017).

The above restrictions (excl. the keyword screening) resulted in an initial sample of 3053 acquisitions. After screening the target business descriptions for high-tech keywords and making smaller adjustments required for the event study and regression model due to data availability, a final sample of 1146 high-tech oriented transactions was obtained. The selection process is illustrated in more detail in Figure 1.

[6] The optimal three-digit SIC codes by Kile and Phillips (2009) are the following: [283] drugs; [357] computer and o ce equipment; [366] communications equipment; [367] electronic components and accessories; [382] laboratory apparatus and analytical, optical, measuring, and controlling instruments; [384] surgical, medical, and dental instruments and supplies; [481] telephone communications; [482] telegraph and other message communications; [489] communications services, not elsewhere; [737] computer programming, data processing, and other computer related services; and [873] research, development, and testing services.

Figure 1. Sample collection process



A control group of takeover announcements with a nontech acquirer and a nontech target was constructed to test whether their takeover announcement cumulative abnormal returns (CARs) differ from those in the high-tech-oriented sample. For the control sample, the selection criteria were the same as for the main sample (e.g., study period, minimum deal size, acquirer and target ownership, and location) except for the target industry classification – all transactions with an acquirer or target firm classified within one of the two-digit SIC codes by Kallunki et al. (2009) as technology-intensive industries were excluded. As a final touch, the acquirer and target business descriptions in the control sample were also screened for the 24 high-tech keywords, and the identified deals were excluded. The final control sample consisted of 2551 nontech acquisitions (see Appendix A3 for descriptive statistics including deal size and announcement returns).

3.2. Variables

3.2.1. Returns

This study uses CARs measured over two days, five days, and eleven days. The two-day event window [0, +1] is the main benchmark window in line with previous windows (Kohers & Kohers, 2000; Benou & Madura, 2005). Longer event windows [-2, +2] and [-5, +5] are also reported to show the possible impact of the window length. The formula for calculating the abnormal returns is:

$$ARit = Rit - E\,(Rit),$$

where AR_{it} = abnormal return for firm *i* at time *t*, R_{it} = actual return for firm *i* at time *t*, and $E(R_{it})$ = expected return for firm *i* at time *t*.

The actual returns are calculated as each acquirer's daily stock returns around the time of the takeover announcement. Due to statistical preferences, the returns are transformed into logarithmic form:

$$Rit = ln \frac{P_{(t)}}{P_{(t-1)}},$$

where $P_{(t)}$ = closing stock price for firm *i* at time *t*, and $P_{(t-1)}$ = closing stock price one business day before time *t*.

The expected returns are calculated using the standard market model (MacKinlay, 1997). The market model uses OLS regressions to estimate the relationship of individual bidder stock returns and a proxy for market returns (R_{mt}) during a chosen estimation period prior to the takeover:

$$E\,(R_{it}) = \alpha_i + \beta_i R_{mt},$$

where α_i measures the individual firm intercept and β_i measures the sensitivity of the firm's stock price to the market index movements. Country-specific stock market indices have been chosen as a proxy for market returns (R_{mt}), which enables accounting for country-specific variations in the expected returns. An estimation period of [-200, -51] has been chosen, which is similar to, e.g., Kohers & Kohers (2000). The CARs used in the regressions are then defined as:

$$\mathrm{CAR}_i = \sum \mathrm{AR}_{\mathrm{it}}.$$

Next, the average daily abnormal returns (AARs) are calculated for the entire sample, after which the cumulative average abnormal returns (referred to as CAAR) can be obtained by adding up all the average abnormal returns within the event window:

$$AAR_t = \frac{\sum_{t=1}^{n} AR_{it}}{n},$$

$$CAAR\,[p, q] = \sum_{t=p}^{q} AAR_t.$$

3.2.2. Variables of M&A characteristics

In order to study the effects of acquirer experience and learning behavior, variables for acquirer frequency and deal order are created (for a discussion, see Laamanen and Keil, 2008). The variable frequent acquirer (FREQUENT ACQUIRER) is defined as firms that announced two or more technology-oriented deals during the studied time horizon. Similar definitions are used by BCG (2017) and Al Rahahleh & Wei (2010). Frequent acquirer takes a value of one in the case of a frequent acquirer deal whereas deals by acquirers with only one announcement are assigned a value of zero.

The variable deal order is employed to explore the value impact of frequent acquisitions in line with Al Rahahleh & Wei (2010). Deal order (DEAL ORDER) ranges from one to the maximum number of serial acquisitions in the sample. As the sample includes both one-time and frequent acquirers, deal order is measured as an interaction variable taking the deal order value only if the acquirer is classified as a frequent acquirer and the value of 0 otherwise. A positive coefficient for the order on CARs could reflect managerial learning behavior and shareholder appreciation of experience while a negative coefficient could indicate that the acquirer's management is affected by managerial hubris and overstate the potential value of tech targets in subsequent deals.

To explore the role of industry and digitalization characteristics, we create four dummy variables. The industrial acquirer variable (INDUSTRIAL ACQUIRER) takes the value of one for acquirer firms with SIC codes 20-39 (Manufacturing) or 15-17 (Construction) and zero otherwise. The services acquirer variable (SERVICES ACQUIRER) takes the value of one if the acquirer is classified within the two-digit SIC codes 70-89 and the value of zero otherwise. Following BCG (2017) and Grossman (2016), these broad sectors were chosen to highlight the two strong but different technology trends in the service and industrial sectors.

To measure the roles of various digitalization-related transaction characteristics, we construct dummy variables for digital deals and software deals. Digital deals (DIGITAL TARGET) and software deals (SOFTWARE TARGET) take the value of 1 for takeover announcements where the target business description contains the corresponding keyword and zero otherwise. These variables are used to explore the influence of specific technologies on the acquisition of high-tech targets. While the word digital is a rather self-explanatory proxy for digitalization, the word software was chosen because of the popularity of software-related targets, which is due to their favorable economics, including scalable products, low deployment costs, and high profit margins (BCG, 2017). These two keywords also appear to be relevant for most industries experiencing digital transformation (see also Appendix A1). For comparison, Benou & Madura (2005) explored the role of the internet and biotechnology & healthcare sectors.

Building on previous research on tech-related or frequent acquisitions, we include a comprehensive set of control variables in all regression models. Benou & Madura (2005) and Al Rahahleh & Wei (2010) show that the performance of large and small transactions tends to differ. Relatedly, BCG (2017) finds that the majority of high-tech acquisitions are worth $100 million or less while a smaller group of large-cap deals is worth more than $500 million. Furthermore, the largest deals seemed to yield clearly more negative returns than the smaller deals. We measure deal size (DEAL SIZE) as the natural logarithm of transaction value, measured in € m. In addition, since Kohers & Kohers (2000) and Goergen & Renneboog (2004) argue that large targets relative to their acquirers contribute to greater synergies and that deals with larger relative size attract more investor attention and publicity and consequently a stronger price impact (Benou & Madura, 2005), we include relative deal size (RELATIVE DEAL SIZE) as a control variable. Relative size is measured relative to the acquirer market value eleven days prior to the event and defined as:

$$Relative\ size = \frac{Transaction\ value}{Transaction\ value + Acquirer\ market\ capitalization_{\ t-11}}$$

Kohers & Kohers (2000) suggest that strong acquirer performance could also be connected to more successful takeovers. To examine acquirer performance, we use return on assets (referred to as BIDDER ROA) calculated as net income divided by total assets. In addition, s*tock-only payment* (STOCK) was chosen as a control variable based on Higgins & Rodriguez (2006) and Kohers & Kohers (2000) who claim that stock financing could offer increased flexibility and may even be the preferable option in technology-oriented takeovers. Private target (PRIVATE TARGET) was chosen to depict the ownership status and the growth stage of the target since more mature firms tend to be listed while younger targets are often privately held. Private targets also tend to be more subject to valuation errors. Cross-border deal (CROSS BORDER) controls for the geographical scope of the takeover and is set equal to one for cross-border acquisitions. For technology-related takeovers, the cross-border nature has been found to have positive wealth effects (Kohli & Mann, 2012). However, the case of nontech acquirers buying tech targets has been studied very little. It is seen as relevant for the study as the sample consists of European acquirers that buy tech targets from all over the world.

As tech-oriented bidders may acquire either smaller or larger stakes in their targets according to their technological needs, it is important to control for the percentage of shares acquired (STAKE). BCG (2017) finds the most successful tech acquirers to be flexible and willing to pursue alternative deal structures, such as minority investments. A larger stake could receive a more positive interpretation from the shareholders as it enables broader control over the target and better exploitation of technological synergies.

Lusyana & Sherif (2016) and Kohers & Kohers (2000) find that investor enthusiasm in high-tech takeovers increases over time. Hence, we include a variable equal to one for *takeovers announced in the year 2012 or later*. The year 2012 was chosen since it periodically divides the sample roughly in half. Moreover, BCG (2017) reports a steady growth pattern (CAGR 2012-2016 of 27%) in global technology M&A volumes starting in the year 2012. Naturally, a positive variable coe cient would be expected, indicating more recently announced transactions to yield higher CARs.

We note that indicator variables for hostile takeovers and competing bids, often used as control variables both in general and tech-related M&A studies, were excluded. The decision was logical as more than 95% of the acquisitions in the sample consisted of friendly takeovers and takeovers with only one bidder.

3.3 Methodology

The regression models take the following form:

Model (1) for industry digitalization characteristics:

$$Y_i = \alpha + \beta * X_i + \gamma_1 * DIGITAL\ TARGET_i + \gamma_2 * SOFTWARE\ TARGET_i + \gamma_3 * SERVICES\ ACQUIRER_i + \gamma_4 * INDUSTRIAL\ ACQUIRER_i + \varepsilon_{i.} \quad (1)$$

Model (2) for acquirer experience:

$$Y_i = \alpha + \beta * X_i + \gamma * FREQUENT\ ACQUIRER_i + \varepsilon_{i.} \quad (2)$$

Model (3) for learning behavior:

$$Y_i = \alpha + \beta * X_i + \gamma * DEAL\ ORDER_i + \varepsilon_{i.} \quad (3)$$

The model variables are as follows:

Y_i: Acquirer 2-day/5-day/11-day CAR at takeover announcement;
α: Constant;
β: Vector of parameters for control variables;
X_i: control variables that typically have explanatory power on takeover CARs: DEAL SIZE, RELATIVE DEAL SIZE, BIDDER ROA, STOCK, PRIVATE TARGET, CROSS BORDER, STAKE, and AFTER2012; and
γ, γ_1-γ_4: Parameters for the main variables.

DIGITAL TARGET$_{i,}$ & *SOFTWARE TARGET*$_i$: indicator variables taking the value of 1 for takeover announcements where the target business description contains the corresponding keyword and 0 otherwise,
SERVICES ACQUIRER$_{i,}$ & *INDUSTRIAL ACQUIRER*$_i$: indicator variables taking the value of 1 for takeover announcements where the acquirer has the defined two-digit SIC industry classification and 0 otherwise,
FREQUENT ACQUIRER$_i$: indicator variable taking the value of 1 if the takeover is announced by a frequent acquirer (acquirers with two or more announced deals) and 0 otherwise,
DEAL ORDER$_i$: takes the value deal order number for firms with 2 or more announced deals, and
ε_i: Disturbance term.

4. Findings

4.1 Univariate tests

Table 1 reports the CAAR percentage for each event window and the significance levels.[7] Panel A shows that the CAAR is positive and statistically significant for all event windows. The highest CAAR is obtained in the five-day event window, amounting to 0.92%; and the CAAR is highly statistically significant. We note that the statistical significance of the results slightly decreases as the window progresses, which indicates that the information content of the returns decreases as we move further away from the announcement day.

7 Explanations of the significance tests are available from the authors.

Table 1. Univariate tests
The sample covers 1146 tech-oriented deals announced by European acquirers during 2006-2019. The control sample includes 2551 nontech takeovers. The test results are for individual t-tests, F-tests for variances and two-sample t-tests. All p-values are calculated assuming two-tailed tests. ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively.

PANEL A. WINDOW LENGTH			
EVENT WINDOW	CAAR	P-VALUE	OBSERVATIONS
[0,+1]	0.82 %***	0.00	1146
[-1,+1]	0.76 %***	0.00	1146
[-2,+2]	0.92 %***	0.00	1146
[-5,+5]	0.59 %**	0.03	1146
[0,+10]	0.57 %**	0.05	1146

PANEL B. TYPE	CAAR [0, +1]	P-VALUE	OBSERVATIONS
Main group	0.82 %***	0.00	1146
Control group	1.13 %***	0.00	2551
One-time acquirers	1.43 %***	0.00	397
Frequent acquirers	0.49 %**	0.01	749
1st deal	1.15 %***	0.01	231
2nd-3rd deal	0.28 %	0.30	347
3rd+ deal	0.49 %*	0.06	287

PANEL C. F-TEST FOR VARIANCES, TWO SAMPLES, CAAR [0, +1]	F-VALUE	P-VALUE	VARIANCES
Main vs. control group	0.935	0.18	Equal
One-time vs. frequent	1.206**	0.03	Unequal
1st vs. 2nd-3rd deal	1.637***	0.00	Unequal
1st vs. 3rd+ deal	2.183***	0.00	Unequal

D. T-TEST, TWO SAMPLES, CAAR [0, +1]	*T*-STATISTIC	P-VALUE	CONCLUSION
Main vs. control group	-1.54	0.12	No difference
One-time vs. frequent	2.68***	0.01	Difference
1st vs. 2nd-3rd deal	1.78*	0.08	Difference
1st vs. 3rd+ deal	1.37	0.17	No difference

With the event study results, we ask whether acquisitions of high-tech targets by nontech firms are perceived to create strategic value for the acquirer shareholders. We find that this is the case, but we note that the positive reaction is quite small (two- and five-day CAARs of approximately 1%), which is in line with the common fact that acquirers only receive small or moderate gains in takeover announcements, if any (e.g., Koller et al., 2010). Relatedly, the technology takeover report by BCG (2017) documented a seven-day CAAR of 0.47% for nontech buyers during 1997-2016.

The individual t-test results (Panel B of Table 1) show that both the main sample and the constructed control group of nontech takeover announcements experience positive and significant two-day CAARs during the study period. Although the CAARs are slightly higher for the control group, the obtained results are very similar and in line with previous findings on acquirer takeover gains. In the experience-based subsamples, both one-time and frequent acquirers receive positive and significant two-day CAARs, although those of frequent acquirers are lower (1.43% vs. 0.49%). The most interesting results are obtained when comparing the subsamples of 1st deal, 2nd-3rd deals and 3rd+ deals of frequent acquirers: the CAARs decrease in subsequent deals. Furthermore, the statistical significance of the CAARs is lower in later deals: while the CAAR of the first announced deal is significant at the 1% level, the second- and third-deal CAARs do not statistically differ from zero. The CAARs of third or later deals are significant at the 10% level (p=0.056).

Prior to the two-sample t-tests, F-tests for sample variances were conducted for each sample pair (Panel C of Table 1). The null hypothesis of equal sample variances was rejected for all sample pairs except for the first pair ("main vs. control group"), which means that the other pairs were next tested with a two-sample t-test assuming unequal variances. For the first sample pair, a two-sample t-test assuming equal variances was conducted.

Panel D of Table 1 presents the results from the two-sample t-tests. As the two-tailed p-values show, the null hypothesis of no difference between the sample means was rejected for "one-time vs. frequent" (significant at the 1% level), indicating that one-time acquirers of technology firms experience significantly higher two-day CAARs at takeover announcements. In addition, there seems to be a significant (10% level) difference between the first deal and second and third deals of frequent acquirers, indicating that there is a somewhat decreasing return pattern in the subsequent deals. Finally, the CAARs in the main and control samples did not seem to materially differ from each other.

The results in Table 1 give us initial tools to examine the research hypotheses on value creation, experience, and learning behavior. Based on the two-sample t-test between the main sample and the control group, there seems to be no material difference in the stock price response to buying a high-technology firm and a traditional firm. However, the reactions are significantly positive, also for tech-oriented takeovers, which gives support to our research hypothesis one. Furthermore, the "one-time vs. frequent" results support the idea that one-time acquirers experience higher shareholder returns than frequent acquirers in tech-oriented takeovers – shareholders appreciate their first initiative to adopt new technology. Finally, the test results from the "1st vs. 2nd-3rd deal" somewhat support the argument that frequent acquirers exhibit managerial hubris in subsequent deals with a declining pattern in the stock price response.

4.2. Regression results

The regression results using CARs in Panel A of Table 2 show that the acquirer sector matters for the success of digital acquisitions. Industrial firms (INDUSTRIAL ACQUIRER) experience significantly higher CARs than other nonindustrial acquirer sectors taken as a whole. However, the industrial sector dummy is only significant in the shortest window. The technological orientation of the target such as digital or software (DIGITAL TARGET or SOFTWARE TARGET) does not significantly affect the returns to high-tech acquisitions. Table 2 also shows that the relative size variable (RELATIVE DEAL SIZE) is positive and statistically highly significant in all models, which implies that the returns increase as the size of the acquisition in relation to the acquirer increases. The returns to private targets (PRIVATE TARGET) are significantly lower than those for public targets.

Table 2. Regressions

The sample covers 1146 tech-oriented deals announced by European acquirers during 2006-2019. Panel A is the sector effects for targets and acquirers. Panel B is on the acquirer frequency, and Panel C is on the deal order. The coe cients for different CAR event windows are displayed. Dummy variables are marked by (D). *t*-statistics are in parentheses below the coe cient estimates. ***, **, and * denote statistical significance at the 1, 5, and 10 % levels, respectively.

	PANEL A. SECTOR EFFECTS			PANEL B. ACQUIRER FREQUENCY			PANEL C. DEAL ORDER		
	[0, +1]	[-2, +2]	[-5, +5]	[0, +1]	[-2, +2]	[-5, +5]	[0, +1]	[-2, +2]	[-5, +5]
Intercept	-0.003	-0.005	0.003	0.005	-0.002	0.006	0.003	-0.002	0.002
	(-0.471)	(-0.659)	(0.300)	(0.889)	(-0.266)	(0.610)	(0.589)	(-0.254)	(0.262)
DIGITAL TARGET (D)	0.010	0.012	0.013						
	(1.381)	(1.403)	(1.294)						
SOFTWARE TARGET (D)	-0.002	-0.009	-0.006						
	(-0.528)	(-1.551)	(-0.855)						
SERVICES ACQUIRER (D)	0.004	0.003	-0.005						
	(0.892)	(0.558)	(-0.655)						
INDUSTRIAL ACQUIRER (D)	0.010	0.007	-0.006						
	(2.048) **	(1.025)	(-0.668)						
FREQUENT ACQUIRER (D)				-0.005	-0.001	-0.009			
				(-1.528)	(-0.274)	(-1.549)			
DEAL ORDER							-0.001	-0.001	-0.002
							(-1.935) *	(-1.147)	(-1.316)
DEAL SIZE (€. ln)	-0.002	-0.002	-0.003	-0.001	-0.001	-0.003	-0.001	-0.001	-0.003
	(-2.182) **	(-1.350)	(-1.895) *	(-1.719) *	(-1.201)	(-1.698) *	(-1.633)	(-1.051)	(1.665) *
RELATIVE DEAL SIZE (%)	0.093	0.084	0.114	0.091	0.086	0.108	0.090	0.083	0.109
	(3.731) ***	(2.702) ***	(2.254) **	(3.568) ***	(2.730) ***	(2.171) **	(3.541) ***	(2.633) ***	(2.146) **
BIDDER ROA (%)	-0.012	0.005	-0.070	-0.013	0.004	-0.070	-0.013	0.004	-0.072
	(-0.582)	(0.155)	(-1.438)	(-0.616)	(0.131)	(-1.450)	(-0.652)	(0.116)	(-1.465)
STOCK (D)	0.004	0.016	-0.010	0.004	0.016	-0.012	0.004	0.015	-0.012
	(0.326)	(1.089)	(0.544)	(0.227)	(1.077)	(-0.648)	(0.270)	(1.052)	(-0.637)
PRIVATE TARGET (D)	-0.007	-0.009	-0.012	-0.007	-0.009	-0.012	-0.007	-0.010	-0.012
	(-1.863) *	(-2.077) **	(-1.867) *	(-1.897) *	(-2.096) **	(-1.818) *	(-1.949) *	(-2.131) **	(-1.852) *
CROSS BORDER (D)	0.003	0.004	0.017	0.004	0.005	0.016	0.004	0.005	0.016
	(0.949)	(0.873)	(2.565) **	(1.251)	(1.058)	(2.483) **	(1.187)	(0.997)	(2.436) **
STAKE (%)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.010)	(1.327)	(0.685)	(1.027)	(1.321)	(0.532)	(1.089)	(1.358)	(0.578)
AFTER 2012	0.004	0.007	0.009	0.003	0.007	0.010	0.004	0.007	0.011
(D)	(1.095)	(1.438)	(1.537)	(0.976)	(1.505)	(1.745) *	(1.278)	(1.714) *	(1.995) **
Normality (Chi-Sq.)	1493.13***	2543.79***	1173.24***	1511.83***	2567.98***	1150.20***	1540.5***	2567.96***	1159-2***
Heteroscedasticity	180.72***	102.51***	453.30***	133.39***	80.76***	380.42***	129.71***	66.63**	389.4***
Adj. R-squared	0.04	0.02	0.03	0.04	0.02	0.03	0.04	0.02	0.03
F-stat.	2.67***	2.38***	1.60*	2.92***	2.42***	2.19**	3.00***	2.55***	2.20**
Observations	1146	1146	1146	1146	1146	1146	1146	1146	1146

Panel B of Table 2 shows that the coe cient for the frequent acquirer variable (FREQUENT ACQUIRER) is negative although not statistically significant. Hence, support for Hypothesis 1 is not obtained. Panel C of Table 2 further shows whether there is a significant learning behavior coming from the number of acquisitions in which the firm is involved. The coe cient for DEAL ORDER is negative and statistically significant in the short-term window but negative and statistically insignificant for the longer event windows. Some evidence is thus obtained for Hypothesis 2b (rather than H2a), stating that the positive announcement CARs decline when experience accumulates. More generally, the results imply that there are reduced benefits after the implementation stages of new high-tech technology. An alternative interpretation, in line with the BCG(2017) result of a smaller initial return for serial acquirers, may be that the market is more positively surprised in the case of first-time acquirers and interprets the first tech acquisition as a signal that the company, e.g., understands the need to transform and hence changes its business model.[8]

The results in Panel B of Table 2 showing a declining return to multiple tech M&As by nontech acquirers give some support to related research strands such as (1) the hubris hypothesis suggesting that managerial overconfidence is reinforced after an initial successful deal (Aktas et al., 2009; Al Rahahleh & Wei, 2010); (2) the idea of a diminishing number of valuable targets or increasing manager aggressiveness (Klasa & Stegemoller, 2007; Aktas et al., 2009); and (3) the learning curve effect as applied to production (see, e.g., Argote and Epple, 1990), which suggests reduced benefits after the implementation stages of new technology. We can describe our results with the general hypothesis of declining benefits to multiple technology M&As. The results imply that the first tech acquisition brings the largest benefits to nontech buyers.

In line with Lusyana & Sherif (2016), Kohers & Kohers (2000), and BCG (2017) who report the increases in investor enthusiasm in high-tech takeovers to increase over time, we find a positive coe cient for the dummy variable indicating the time period after 2012, indicating that more recently announced transactions are associated with higher CARs. The positive sign is as expected, but the variable is statistically significant only in some specifications in Table 2.

5. Conclusions

This study explores whether acquirer shareholders in traditional, nontechnological sectors perceive the strategic decision to buy a high-technology target as value-enhancing. The motivation of the research focus is that digitalization-increasing M&As have received limited attention in the literature.

This paper uses a sample of 1146 high-tech oriented M&A deals announced by European acquirers during the period from 2006-2019. High-tech keywords were used to identify digital takeovers. Acquirers in the industrial sector – compared with services, transportation, financial, retail and other – gain the most from adding high-tech to their firm portfolios. The study finds that one-time acquirers experience significantly higher cumulative abnormal returns than frequent acquirers. Moreover, there are slightly decreasing returns for subsequent deals, which suggests that there are reduced benefits after the implementation stages of new high-tech technology or that the first tech acquisition signals something beyond the deal itself, such as a new strategical orientation rewarded by the market.

The findings imply that European acquirer shareholders perceive acquiring advanced and digital technologies as an equally important strategic decision as traditional acquisitions, de-

[8] For serial acquirers, there may already be an expectation of more value enhancing tech acquisitions built into their stock prices.

spite having different synergistic goals. Moreover, the role of tech-oriented acquisitions seems to be increasingly important over time, reflecting the evolving digital maturity, especially in Europe. When separately examining identified software and digital targets, within-industry differences were not found to have an impact on the valuations of tech-oriented acquisitions. However, industrial acquirer companies were found to earn higher two-day cumulative abnormal returns than other sectors. The positive investor perception could be a consequence of newly evolving needs in industrial technology, including embedded intelligence, IoT, advanced analytics and machine learning, having direct and measurable impacts on process e -ciency, competitiveness and supply chain cooperation.

As noted in BCG (2017), the share of transactions involving a high-tech target has been growing faster than the overall M&A market, and what is particularly intriguing is that this part of the market is increasingly characterized by firms operating in nontechnological sectors buying high-tech companies. These firms strive to gain access to vital new technologies that are disrupting their industries and aim to close innovation gaps by substituting or complementing their in-house R&D.

This study gives support to the idea that M&As are a credible part of the digitalization process (from a shareholder perspective), providing insights into situations where tech M&As appear to be particularly beneficial. One should note that the new digital forces will continue to emerge and that it will be vital for business leaders to understand the different stages and options along the digital journey and their impacts on firm value.

Future research could compare the short- and long-term performance of tech-focused takeovers. Other dimensions in takeovers that deserve more analysis include sectoral variation (e.g., B2B vs. B2C and digitally immature vs. mature sectors), different technologies (e.g., fintech, big data, and cloud technology) and different acquirer and target characteristics. Finally, as digitalization-driven acquisitions are only one way to adopt new technology and a single tool to support a comprehensive digital strategy, future research could consider other options such as digitalization-motivated strategic alliances (see also, Lee & Lim, 2006).

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Appendix A1. High-tech keywords

The table reports the high-tech keywords used in the sample selection process (with the number of hits in target business descriptions in parentheses).

KEYWORDS FOR HIGH-TECH BASED ON BCG (2017)	
Analytics (31)	Fintech (1)
Big data (2)	Intelligence (19)
Blockchain (1)	Intelligent (13)
Business Intelligence (5)	Internet (56)
Cloud (26)	Mobile (115)
Data (133)	Mobility (7)
Data analysis (3)	Online (148)
Data center (7)	Platform (89)
Digital (116)	SaaS (4)
e-Commerce (11)	Smart (20)
e-Learning (2)	Software (177)
Electronic (99)	Tech (423)

Appendix A2. Deal and acquirer statistics by acquirer country

The table reports the deal volume, frequent deals, average deal size and average relative market value of the target as a fraction of the acquirer.

ACQUIRER COUNTRY	DEAL VOLUME	FREQUENT DEALS	DEAL SIZE (€ M)	RELATIVE DEAL SIZE
United Kingdom	491	353	113.3	9.7 %
Sweden	112	63	88.6	6.1 %
France	101	74	368.6	6.7 %
Germany	93	58	779.4	7.1 %
Italy	50	31	18.4	8.3 %
Netherlands	45	33	220.9	7.7 %
Norway	36	19	46.2	5.7 %
Spain	31	16	139.7	6.2 %
Finland	30	15	66.8	7.8 %
Ireland	29	23	209.1	3.5 %
Poland	28	14	35.7	7.2 %
Switzerland	22	9	444.3	10.8 %
Malta	13	13	22.2	3.5 %
Belgium	11	7	696.3	7.0 %
Austria	9	4	99.4	7.0 %
Denmark	9	4	41.2	4.3 %
Russia	8	2	19.1	1.8 %
Luxembourg	7	6	96.4	5.2 %
Portugal	5	0	152.2	9.7 %
Turkey	4	0	212.4	16.8 %
Cyprus	4	3	4.5	3.8 %
Greece	3	0	20.2	14.7 %
Gibraltar	2	2	53.4	14.7 %
Kazakhstan	1	0	1.0	0.3 %
Iceland	1	0	1.5	0.2 %
Bulgaria	1	0	2.0	1.6 %
Total	1146	749	194.4	8.0 %

Appendix A3: Descriptive statistics of the control sample

The table reports the descriptive statistics for the control sample of 2551 nontech takeovers.

	DEAL SIZE (€ M)	CAR [0, +1]	CAR [-2, +2]	CAR [-5, +5]
Mean	331.8	1.1 %	1.2 %	1.0 %
Minimum	1.0	-53.0 %	-60.8 %	-153.5 %
Maximum	74 734.7	59.3 %	70.8 %	85.3 %
Median	32.0	0.6 %	0.8 %	0.9 %
Mode	20.0	0.6 %	0.8 %	0.8 %
Std. Dev.	2 130.9	5.7 %	7.1 %	10.1 %
Skewness	24.6	1.2	0.6	-1.9
Kurtosis	762.5	17.7	13.9	36.2