Technology-motivated Acquisitions and the Real Option Portfolio of Non-tech Firms*

Markus Fütterer, Marc Steffen Rapp, Michelle Schlosser

We are interested in "access to technology" acquisitions of non-tech firms and propose a novel approach to identify such acquisitions, which we call technology-motivated acquisitions (TMA). Studying a large sample of European non-tech firms, we document an increasing importance of TMA deals and empirically examine the role of such deals in firms' real option portfolios. We find that firms investing in their real option portfolios are more likely to engage in TMA, a pattern that is more pronounced in firms with high financial flexibility. Furthermore, engaging in TMA significantly improves the value of firms' real option portfolios, in particular, for small and focused firms. We identify TMA using a novel dictionary covering (i) perspectives from academic literature, (ii) publicly available emerging technology lists, and (iii) suggestions from practitioners.

> "The disruptive effect of technology companies has propelled non-technology companies to explore opportunities outside of their core sectors of expertise."
> **Citi Group (2018), Disruptors at the Gate.**

Markus Fütterer, Ph.D., is Manager at WTS Deutschland, Germany.
Marc Steffen Rapp is a Professor of Business Administration at Philipps-Universität Marburg, Germany, and a Professor at the Center for Corporate Governance at Copenhagen Business School, Denmark.
Michelle Schlosser, Ph.D., is a Strategic Controller and Corporate Developer at Geschwister Oetker Beteiligungen KG, Germany.

* We appreciate helpful comments from Federico Magno, Jens Pfeifer, Andrew Reek, Philipp Schaller, and an anonymous reviewer. During the revision of the manuscript the authors used ChatGPT in order to improve readability. After using the tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article. The usual caveat applies.

1 Introduction

What is the importance of the "access to technology" motive for acquisitions by non-tech firms? When do non-tech firms engage in technology-motivated acquisitions (TMA) and what are the consequences of TMA? For many years, scholars from different disciplines have been challenged by these questions (Frey and Hussinger 2006 for non-tech firms; or Hanelt et al. 2021; Christensen et al. 2011; Kohers and Kohers 2000, Canace and Mann 2014). We add to this debate by taking the view of a strategist interested in the role of TMA for a firm's real option portfolio (Grullon et al. 2012; Lee et al. 2018; Rossi et al. 2013).[1]

Emerging technologies threaten existing business models but also provide the potential for "creative destruction".[2] The challenge is to get access to these emerging technologies. One potential avenue in that regard is to engage in what we call a *technology-motivated acquisition* (TMA), i.e., an acquisition where the target firm has access to the technology.[3] In a recent survey among "representatives of leading industrial firms, investment banks, and investors," A.T. Kearney (2019) finds that executives consider "technology access" to be the most important driver of M&A activity (see Figure 1). Other professional service firms have found similar results.[4]

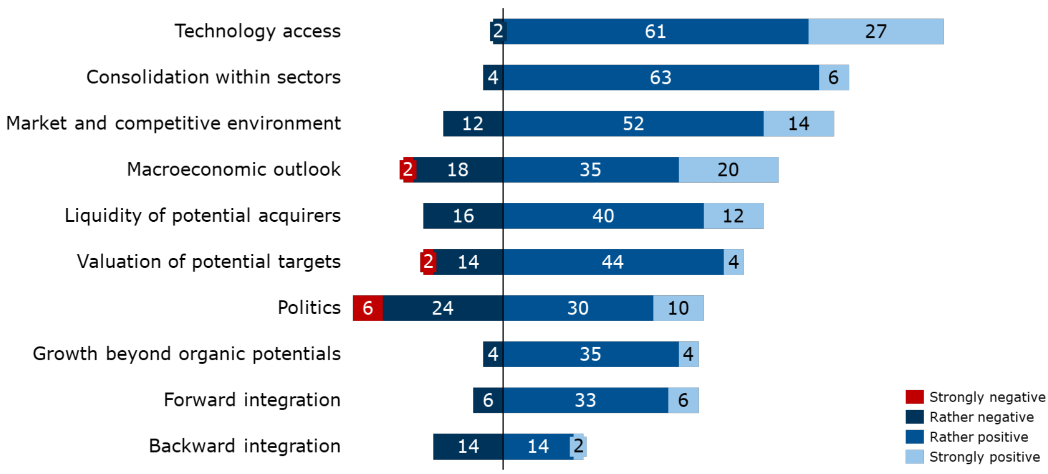

Figure 1: Deal rationales as reported by A.T. Kearney's Industrials Executive Mergers and Acquisitions Report 2019

Notes: This figure reports the result of a survey conducted by the consulting firm A.T. Kearney among "representatives of leading industrial firms, investment banks, and investors in January and February 2019." (See A.T. Kearney, 2019).

1 We take an empirical approach here following the lines of Grullon et al. (2012) and Lee et al. (2018). Others approach the issue from a theoretical (or case-based) perspective. See for instance, Ulrich (2013).
2 "Creative destruction (German: schöpferische Zerstörung), sometimes known as Schumpeter's gale, is a concept in economics that since the 1950s is the most readily identified with the Austrian-born economist Joseph Schumpeter who derived it from the work of Karl Marx and popularized it as a theory of economic innovation and the business cycle." (Wikipedia, 2022).
3 The literature has identified a variety of merger motives, e.g., access to customers, products, or markets (Calipha et al. (2010); Barkema and Vermeulen 1998), access to technology (BCG 2017; Presutti et al. 2006), etc. See A.T. Kearney (2019) for a survey.
4 For instance, DLA Piper finds in a survey from 2020 that "access to new technology" is the "most beneficial feature from the acquisition of an external company" (see DLA Piper 2020).

To study the “access to technology” acquisition motive for a large sample of firms, we propose a novel approach to identify TMAs. Specifically, we suggest applying textual analysis to descriptions of the deal synopsis and the business model of the target firm based on a novel dictionary covering (i) perspectives from academic literature, (ii) publicly available emerging technology lists, and (iii) suggestions from practitioners.[5] Constructing such a dictionary allows us to identify TMAs for a large panel of European listed non-tech firms and to study the role of TMA in a firm’s real option portfolio.

A firm’s *real option portfolio* refers to its set of “discretional business opportunities”. More specifically, a *real option* or *strategic option* refers to the right (but not the obligation) to decide in the future to realize a specified business activity at a specified cost (Trigeorgis and Reuer 2017). Pioneered by Myers (1977), the idea of real options has become increasingly accepted in research and practice, specifically in situations characterized by highly uncertain environments, for instance, in the case of investments in new technologies (e.g., Anand et al. 2017).

A firm’s real option portfolio may consist of different types of real options. Trigeorgis and Reuer (2017) describe categories of real options referring to organizational flexibility (e.g., the option to scale production or switch suppliers) and investment opportunities (e.g., the option to grow in existing or to enter new markets). Anand et al. (2017) argue that there might be a trade-off between switching options and study theoretical determinants of the value of a firm’s real option portfolio. Empirically, the value of a firm’s real option portfolio is often measured by the firm’s real option intensity, which is the firm-specific sensitivity of firm value to uncertainty, where the latter is proxied by changes in firm-level stock return (e.g., Grullon et al. 2012; Lee et al. 2018).

To study the role of TMA in firms’ real option portfolios, we draw accounting, market, and M&A data for all listed European non-tech firms residing in the EU17 countries over the 2001 –2020 period. This gives us an unbalanced panel of 71,731 firm-year observations and 53,454 access-of-control acquisitions. In the first step, we classify the acquisitions as TMA. Therefore, we generate a novel dictionary aiming to capture “emerging technologies” which covers (i) perspectives from academic literature, (ii) publicly available emerging technology lists, and (iii) suggestions from practitioners. We then use this dictionary and classify an acquisition as a TMA in case one of the “emerging technologies” recorded in our dictionary appears either in the deal synopsis or the description of the target´s business model. Overall, we find that 14% of our deals classify as TMA.

In a second step, we examine which firms are more likely to engage in TMA. Specifically, we study the role of real options and leverage. *First*, we argue that TMAs, which provide access to emerging technologies and thus a pathway for “creative destruction”, may be more valuable in case of higher organizational flexibility, more investment opportunities, and thus for firms with more valuable real option portfolios (Grullon et al. 2012; Trigeorgis and Reuter 2017; or Lee et al. 2018). In the empirical analysis, we follow the approach of Grullon et al. (2012) and Lee et al. (2018) and proxy the value of a firm’s real option portfolio by its real option intensity (RI). As such, we hypothesize that RI represents a determinant for TMA activity. *Second*, we argue that leverage might play an important role in the real option-TMA nexus. McConnell and Servaes (1995) find a negative relation between leverage and firm value for growth firms, and Harford et al. (2009) document that firms re-adjust their capital structure after acquisitions. In the context of TMA, we conjecture that a firm’s real option portfolio is more important in

5 Textual analysis has become increasingly common in the economics and business literature. See for instance, Gentzkow et al. (2019); Loughran and McDonald (2016); or Merrick (2015).

case the firm has sufficient financial means to eventually exercise the real options. Arguing that spare debt capacity represents a proxy for financial flexibility, we hypothesize that RI is more (less) important for firms with low (high) leverage.[6]

In a third step, we analyze whether firms that undertake a TMA benefit in terms of an increase in the value of their real option portfolio.[7] The literature has shown that firms can actively invest in their real option portfolio, either organically (CAPEX, R&D) or inorganically using M&A, and increase the value of their portfolio of real option or their *real option intensity* (RI) (Anand et al. 2007; Grullon et al. 2012; McGrath and Nerkar 2004; Cheng 2016).[8] We argue that TMAs might be particularly valuable in this respect, specifically for non-tech firms. Indeed, TMA might provide valuable complementary additions and novel opportunities to non-tech firms outside their core business and hence add to firms' real option portfolios (e.g., McGrath and Nerkar 2004; Rossi et al. 2013). As such, we hypothesize that TMA will increase the value of firms' real option portfolios.

Our results are threefold. First, we document that the relative importance of TMA increased significantly over the last 20 years within our sample covering listed firms from seventeen European countries, culminating in 2020, when 21.1% of all M&A transactions classify as TMA. Second, we find that non-tech firms with high RI are more likely to engage in TMA. A one standard deviation increase in RI significantly increases the odds of engaging in TMA in the next period by 5%. Consistent with intuition, the effect is greater (12%) for firms with lower leverage, suggesting that higher debt capacity or higher financial flexibility facilitates TMA activity.[9] *Third*, we show that non-tech firms engaging in TMA demonstrate a significantly higher RI two years after the deal compared to the event year. The positive TMA effect of 0.072 represents 60% of the mean RI, suggesting economic importance. In line with intuition, the pattern is more pronounced for smaller and more focused firms with limited growth option potential.

Of course, our empirical analysis is prone to several endogeneity concerns. As such, we also examine the robustness of our results and find that they are robust to (i) controlling for deal characteristics commonly discussed in the literature, (ii) matching based on RI characteristics, as well as (iii) taking into account the fact that "engaging in a TMA" is a choice variable by analyzing withdrawn TMA deals.

We contribute to literature along three dimensions. *First*, we identify real option considerations as an additional explanation for the increased interest in TMA by non-tech firms (e.g., Ihamuotila et al. 2021). *Second*, integrating a real options perspective on TMA allows for a more holistic view of acquisition gains beyond product innovation, often measured by new patents (e.g., Hanelt et al. 2021). *Finally*, our findings complement the understanding of real options around investments, as we confirm the proposed development of RI found in the literature (e.g., Grullon et al. 2012) and extend this stream by considering the business model of the target firm as a decisive factor to increase RI (e.g., Cheng 2016).

6 The argument here is that today's leverage determines tomorrow's borrowing capacity of a firm (e.g., Rapp et al. 2014).

7 Many studies focus on (short-term) performance implications of acquisitions. For instance, Morck et al. (1990) and many others document that diversifying acquisitions destroy shareholder value (in the short run). Fernandes (2019) studies why M&A transactions often fail to create value and proposes five "golden rules" to mitigate the problem. We are interested in the effect of TMA for a firm's real option intensity.

8 One might argue that undertaking investments corresponds to the exercise of real options and thus might decrease the value of the portfolio of real options. However, the idea is that some investments create new real options that outweigh the loss due to the exercise of the initial real option (see Trigeorgis and Reuer 2017).

9 Increasing the mean probability to invest in TMA from 6% to 11%, or 18% respectively.

The remainder of this paper is organized as follows. Section 2 introduces the sample and the data. Specifically, it introduces our approach to identifying TMAs. Section 3 introduces the empirical approach, provides the results of our empirical analysis and discusses their robustness. Finally, Section 4 concludes.

2 Sample and data

2.1 Sample construction

We draw our data from Refinitiv (Datastream and the Securities Data Company (SDC) database) in four steps. First, we define the sample to cover European firms. We consider the analysis of European firms to be particularly interesting due to the relatively lower levels of technology adoption among these firms compared to their counterparts in other regions (e.g., Rückert et al., 2020). This creates a "technology gap" (e.g., Smith et al., 2022; Schnabel, 2024) with implications for economic growth (e.g., Krueger and Kumar, 2004). Specifically, we define the sample to cover firms from EU17 countries[10] and restrict the sample to listed firms because we need relatively detailed information on firms' market values to estimate their real option intensity.

Second, we follow the process described in Hanauer (2014) and identify all firms in the Refinitiv universe incorporated and listed in *one of the sample countries during the sample period 2001–2020. Third*, we follow the standard procedure of corporate finance studies and eliminate financial and utility firms. Focusing on non-tech firms, we also eliminate high-tech firms based on the classification proposed by Galindo-Rueda and Verger (2016).[11] Moreover, we eliminate firm-year observations with missing, negative, or zero total assets, total sales, and total shareholder's equity. This gives us an unbalanced panel of 71,731 firm-year observations from 7,338 firms. Fourth, we identify all access-of-control acquisitions by these firms reported by SDC.[12] Access-of-control acquisitions are acquisitions of independent firms where the acquirer owns less than 50% of shares before the transaction and more than 50% after the transaction (Martynova and Renneboog, 2011). We identify 53,454 deals from SDC, which were restricted according to the same specifications as the accounting data (Hanauer 2014). We then merge the deals to the panel data based on the announcement-year of the transaction. The resulting dataset contains 39,009 firm-year observations.

10 The EU17 countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

11 Several authors have developed classification schemes to identify "high-tech firms". We follow Galindo-Rueda and Verger (2016) in our baseline analysis. We re-run the main analysis using the classification of Klasa et al. (2009). Results, which are available upon request, remain robust.

12 We also include deals of non-listed acquirers when the corresponding ultimate parent is publicly listed, frequently representing the actual acquirer.

Table 1: Identified TMA deals per country

Notes: This table reports the distribution of technology-motivated deals across countries and time. We draw deals from Refinitiv, clean the data as described in Section 2.1, and identify technology-motivated deals as described in Section 2.2.

COUNTRY	´01	´02	´03	´04	´05	´06	´07	´08	´09	´10	´11	´12	´13	´14	´15	´16	´17	´18	´19	´20	TOTAL
Austria	3	1	3	0	2	2	2	4	1	3	2	1	2	1	1	3	3	0	1	1	36
Belgium	1	1	2	6	0	7	9	5	4	8	5	1	5	6	9	2	5	4	1	2	83
Denmark	3	4	4	4	5	5	9	3	6	2	4	2	1	3	3	9	2	5	4	1	79
Finland	12	10	5	7	7	8	15	13	10	14	5	6	7	6	13	17	10	9	7	7	188
France	47	33	33	30	46	57	66	63	47	43	52	43	36	53	60	60	60	48	36	38	951
Germany	44	23	23	14	36	43	56	46	52	34	46	37	35	39	33	41	55	53	36	22	768
Greece	3	1	0	1	0	2	3	1	1	3	2	1	1	1	0	0	3	0	0	1	24
Ireland	5	2	0	0	0	4	4	1	0	0	0	0	0	0	0	0	1	0	1	1	19
Italy	12	5	7	9	15	13	13	9	4	5	12	3	3	8	13	18	13	22	15	22	221
Luxembourg	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	4
Netherlands	16	11	10	10	19	13	25	19	10	16	12	9	6	10	7	11	9	3	8	7	231
Norway	16	4	7	12	15	12	28	10	4	12	7	6	7	9	11	6	8	4	9	14	201
Portugal	3	0	0	0	0	1	6	3	3	0	2	0	0	1	0	2	0	0	1	1	23
Spain	3	3	1	2	3	5	14	8	3	6	3	7	5	10	5	2	3	14	12	9	118
Sweden	11	11	4	11	36	34	35	21	13	29	31	26	33	24	30	38	46	48	46	70	597
Switzerland	4	6	7	4	9	11	13	16	17	12	9	9	7	10	18	7	16	8	13	13	209
United Kingdom	103	58	60	73	95	120	131	105	66	69	62	81	75	89	75	68	68	60	50	47	1,555
TOTAL	**286**	**174**	**166**	**183**	**289**	**338**	**429**	**327**	**241**	**256**	**254**	**232**	**223**	**270**	**278**	**285**	**302**	**278**	**240**	**256**	**5,307**

Figure 2 reports the proportion of TMA deals along the EU17 countries. With a share of approximately 29% (10,978 deals), the UK accounts for the largest number of acquisitions, followed by France (17%) and Germany, with almost 12% of transactions. With 31% of tech-motivated deals, Luxembourg leads the way in the TMA segment (due to the low number of deals, this could potentially be considered negligible), followed by Germany, where 18% of deals are technology-motivated, and Norway, with 16% of deals being TMA.

2.2 Identifying tech-motivated deals

Our aim is to identify tech-motivated deals. Therefore, we draw on the method of textual analysis and conduct the deal classification using a dictionary-based approach. Specifically, we proceed in three main steps. *First*, we construct a dictionary of tech terms, i.e., a collection of terms characterizing (emerging) technologies. The dictionary aggregates terms from

- academic literature (Chen and Srinivasan 2019; Garcia de Lomana et al. 2019; Hanelt et al. 2021; Kindermann et al. 2020),
- publicly available technology-related lists (following Bonaccorsi et al. 2020; Joung and Kim 2017), namely the annual MIT list of *10 Breakthrough Technologies*, Wiki lists on *Emerging Technologies*, Gardner's *Top 10 Strategic Technology Trends*, and Scientific American's *Top 10 emerging technologies*,
  and
- suggestions from business experts.

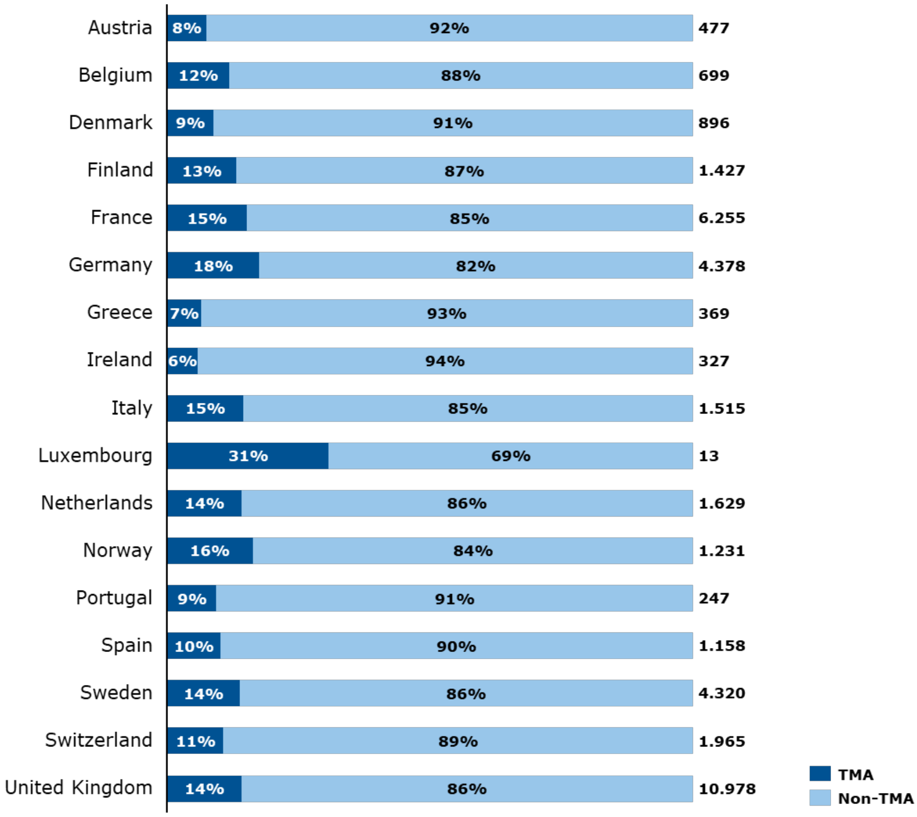

Figure 2: Distribution of TMA deals per Country

Notes: This figure reports all extracted and technology-motivated deals in all EU17 countries. The countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom. For a detailed summary of TMA deals over the sample years 2001–2020 see Table 1.

Each keyword in the dictionary is converted to lowercase characters, word endings are adjusted to allow for multiple word forms, and connotations and other notations are added whenever appropriate.[13] The resulting dictionary contains 759 unique keywords which can be allocated to three main categories – *digital*, *product and process improvement*, and *environment*, as provided in the Appendix.

Second, we construct a deal summary for each identified deal. The deal summary provides the text to classify the transaction as tech-motivated. Relying on all relevant transaction information disclosed by SDC, we aggregate all textual information contained in the variables "Target Business Description" and "Deal Synopsis". In addition, we remove company names as a precautionary measure. For example, any acquirer that includes "software" in its company name could potentially lead to misclassification of the deal and is therefore removed.

Third, using the Linguistic Inquiry and Word Count (LIWC) from Pennebaker et al. (2015), we analyze the deal summaries and classify a transaction as a tech-motivated deal if the summary includes at least one of the tech-related terms from our dictionary. Overall, we find that 14% of our deals classify as TMA. See Table 1 and Figure 2 for an overview.

13 While this includes adding "3-D printer" not only "3D printer" this also addresses language spelling differences, such as "internet of behavior" and "internet of behaviour".

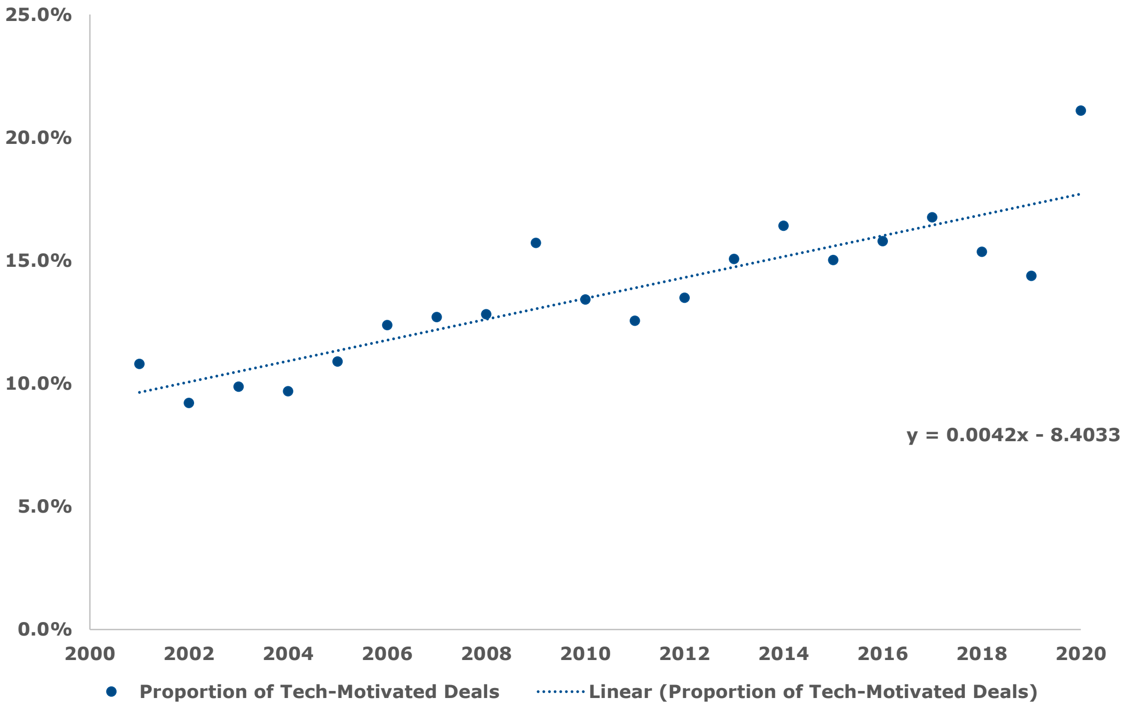

Figure 3: Development of TMA of non-tech firms

Notes: This figure illustrates the proportion of technology-motivated deals and their development over the years 2001–2020 in EU17 countries. The countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

As presented in Figure 3, the relative importance of TMA of non-tech acquirers increased significantly over the last 20 years within our sample covering listed firms from seventeen European countries. More specifically, examining the fraction of M&A transactions that classify as a TMA, the relevance of TMA nearly doubled from 2001 (10.8%) to 2020 (21.1%) with a cyclical but steady trend (a linear regression suggests an average annual increase in the proportion of TMA of 0.42 basis points per year).

2.3 Real option intensity

We measure RI as the annual firm-specific sensitivity of stock returns to changes in stock return volatility, following Lee et al. (2018), by estimating

$$r_{(i,t)}-r_{(f,t)}=a_t+\beta\Delta Volatility_{(i,t)}+\gamma\eta_{(i,t)}+\sum\delta X_{(i,t)}+\varepsilon_{(i,t),} \qquad (1)$$

where $r_{(i,t)}-r_{(f,t)}$ is the weekly excess return of firm i in week t, $\Delta Volatility_{(i,t)}$ is the difference in volatility between week t and t–1 for firm i (based on daily returns within a week), $\eta_{(i,t)}$ represents the market factor loading estimated on daily information in a given month, and $X_{(i,t)}$ embodies a vector of firm controls known at the beginning of a given week for firm i. These control variables are: ln(1+Book Equity/Market Equity), ln(1+Market Equity), the six week lagged return and weekly trading volume per number of shares. a_t is the constant and $\varepsilon_{(i,t)}$ is the error term. We estimate equation 1 separately for each firm-year, to obtain a firm-specific β estimate, which is our measure of RI.

2.4 Summary statistics

We use accounting and market data from Refinitiv, OECD, World Bank, and the European Central Bank to measure deal, firm, and country characteristics. Table 2 presents the control variables separately for the firm-level (Table 2, Panel A) and the deal-level (Table 2, Panel B) analysis. The mean firm shows a RI of 0.16, has 3,320 million EUR in total assets, leverage of 21%, has a positive cash flow of 4% of total assets, which exhibits a volatility of 6% per year, and

Table 2: Summary statistics

Notes: This table provides definitions for variables for the panel data perspective (firm-year level) in Panel A and the deal data perspective (deal event-year level) in Panel B. Firm-level and deal-level data is downloaded from Refinitiv. Country-level data is drawn from OECD, World Bank, and the European Central Bank. All non-dichotomous firm level variables are winsorized by year at the 1% and 99% threshold, to mitigate concerns of outliers. The corresponding samples are constructed as described in section 2. Variables are defined in Table 7.

VARIABLE	N	MEAN	STD	P25	MEDIAN	P75
Panel A: Panel-data perspective						
TMA	39,009	0.06	0.24	0.00	0.00	0.00
Real Option Intensity (RI)$_{(t-1)}$	39,009	0.16	0.67	-0.29	0.15	0.60
Size$_{(t-1)}$	39,009	12.45	2.12	10.91	12.23	13.88
Leverage$_{(t-1)}$	39,009	0.21	0.16	0.06	0.19	0.32
Cash Flow$_{(t-1)}$	39,009	0.04	0.14	0.03	0.06	0.09
Cash Flow Volatility$_{(t-1)}$	39,009	0.06	0.09	0.02	0.03	0.06
Tobin´s Q$_{(t-1)}$	39,009	1.99	1.89	1.01	1.42	2.21
Payout$_{(t-1)}$	39,009	0.67	0.47	0.00	1.00	1.00
Negative Net Income$_{(t-1)}$	39,009	0.23	0.42	0.00	0.00	0.00
Capex$_{(t-1)}$	39,009	0.04	0.05	0.01	0.03	0.06
R&D/Assets$_{(t-1)}$	39,009	0.02	0.05	0.00	0.00	0.01
Loan Spread$_{(t-1)}$	39,009	1.56	0.43	1.32	1.55	1.72
Panel B: Deal-data perspective						
TMA	12,731	1	0	1	1	1
Real Option Intensity (RI)	12,731	0.12	0.71	-0.36	0.15	0.61
Size$_{(t-1)}$	12,731	13.70	2.55	11.68	13.46	15.63
Book-to-Market$_{(t-1)}$	12,731	0.40	0.23	0.23	0.36	0.50
Long Term Leverage$_{(t-1)}$	12,731	0.14	0.13	0.02	0.12	0.21
lnR&D$_{(t-1)}$	12,731	5.09	5.53	0.00	0.00	10.20
Diversification$_{(t-1)}$	12,731	1.33	0.50	1.10	1.39	1.61
Payout$_{(t-1)}$	12,731	0.75	0.43	1.00	1.00	1.00
Trading Volume$_{(t-1)}$	12,731	0.00	0.01	0.00	0.00	0.00
Firm Age$_{(t-1)}$	12,731	3.55	0.97	2.89	3.43	4.39
Cash Flow$_{(t-1)}$	12,731	0.06	0.09	0.04	0.07	0.10
Cash Flow Volatility$_{(t-1)}$	12,731	0.07	0.15	0.02	0.03	0.07
Cash Holdings$_{(t-1)}$	12,731	0.18	0.13	0.08	0.14	0.23
Tangibility$_{(t-1)}$	12,731	0.11	0.13	0.03	0.06	0.14
Closely Held Shares$_{(t-1)}$	12,731	2.93	1.23	2.31	3.32	3.91
Deal Experience$_{(t-1)}$	12,731	7.70	10.78	0.00	4.00	11.00
GDP per Capita$_{(t-1)}$	12,731	10.67	0.13	10.60	10.63	10.72

Tobin´s Q of 1.99. 67% of firms pay dividends and 23% exhibit negative net income. The average firm invests 4% of total assets in Capex, 2% in R&D, and has a loan spread of 1.56%. All non-dichotomous firm level variables are winsorized by year at the 1% and 99% thresholds to mitigate concerns of outliers.

3 Empirical results

3.1 The likelihood to engage in TMA

We examine the likelihood to engage in a TMA in the next period based on the following logistic regression:

$$TMDeal_{(t+1)}=a_0+\beta_1 RI_{(i,t)}+\sum\beta_{(2,i)}X_{(i,t)}+\beta_3\eta_i+\beta_4\varphi_t+\varepsilon_{(i,t)}, \quad (2)$$

where $TMDeal_{(t+1)}$ represents a dummy equal to one in case a TMA is performed in the next period.[14] $RI_{(i,t)}$ is real option intensity, $X_{(i,t)}$ represents a vector of lagged control variables, mainly inspired by Bauguess and Stegemoller (2008) and extended with R&D expenditure as a further determinant of TMA (e.g., Xie et al. 2018).[15] The term η_i describes firm fixed effects to capture time-invariant firm-specific heterogeneity, φ_t are year-effects controlling for unobserved time-varying shocks affecting deal activity.

Table 3 reports our results. In Specification 1.A, we only control for firm size and leverage, as well as year, industry, and country fixed effects.[16] Firm size and leverage are known to be important determinants of M&A activity (e.g., Bauguess and Stegemoller 2008; Caprio et al. 2011). In Specification 2.A we add additional firm characteristics, and in Specification 1.C we allow for firm fixed effects. Consistent with our hypothesis, we find a statistically significant positive coefficient for real option intensity in all three specifications. Also, the correlation is meaningful in economic terms. According to Specification 1.B, increasing RI by one standard deviation increases the odds of engaging in TMA in the next period by 5 percentage points. In other words, the propensity of performing an TMA rises from 6% to 11%.

14 The results remain qualitatively consistent when applying an ordered logit regression model, replacing the TMA deal dummy by the actual number of technology-motivated deals in the next period.
15 The controls consist of Size, Leverage, Cash Flow, Tobin´s Q, Payout, Loss, Capex, R&D and Loan Spread as defined in Table 7.
16 We define industry affiliation following the 10 industry portfolios by Eugene Fama and Kenneth R. French. See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for details.

Table 3: Probability to engage in tech-motivated M&A

Notes: This table presents the results of logit regressions of the effect of RI on the probability of engaging in a TMA deal in the next period. Specification 1.A presents the baseline results with firm size, leverage, year, industry and country effects as the only controls. Specification 1.B allows for further controls (Leverage, Cash Flow, Tobin's Q, Payout, Negative Net Income, Capex, R&D, and Loan Spread) following Bauguess & Stegemoller (2008). Specification 1.C allows for firm fixed effects. Specifications 2.A–2.C follow the logic of 1.A to 1.C, but simultaneously allow leverage to moderate the correlation between RI and future TMA activity. All non-dichotomous firm-level variables are winsorized by year at the 1% and 99% threshold, to mitigate concerns of outliers. All independent variables are lagged by one period. All variables are defined in Table 7. The t-statistics in parentheses are based on robust standard errors, clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

SPECIFICATION	1.A	1.B	1.C	2.A	2.B	2.C
SAMPLE	NON-TECH FIRMS	NON-TECH FIRMS	NON-TECH FIRMS	NON-TECH FIRMS	NON-TECH FIRMS	NON-TECH FIRMS
DEPENDENT VARIABLE	TMA	TMA	TMA	TMA	TMA	TMA
METHOD	LOGIT REGRESSION	LOGIT REGRESSION	LOGIT REGRESSION	LOGIT REGRESSION	LOGIT REGRESSION	LOGIT REGRESSION
Real Option Intensity [RI] $_{(t-1)}$	0.092*** (2.73)	0.079** (2.35)	0.088** (2.13)	0.191*** (3.75)	0.166*** (3.30)	0.189*** (2.88)
Leverage$_{(t-1)}$ x RI				-0.542** (-2.46)	-0.470** (-2.20)	-0.542** (-1.99)
Leverage$_{(t-1)}$	-1.353*** (-5.17)	-0.733*** (-2.77)	-1.382*** (-3.46)	-1.266*** (-4.71)	-0.659** (-2.44)	-1.295*** (-3.21)
Firm Size$_{(t-1)}$	0.414*** (16.63)	0.418*** (16.02)	0.249*** (3.04)	0.413*** (16.60)	0.417*** (15.98)	0.253*** (3.09)
Cash Flow$_{(t-1)}$		0.472 (1.57)	-0.094 (-0.27)		0.462 (1.54)	-0.109 (-0.32)
Cash Flow Volatility$_{(t-1)}$		1.131*** (3.37)	0.196 (0.32)		1.120*** (3.34)	0.185 (0.30)
Tobin´s Q$_{(t-1)}$		0.038*** (2.75)	0.078*** (3.88)		0.037*** (2.72)	0.078*** (3.86)
Dividends$_{(t-1)}$		-0.086 (-1.16)	0.057 (0.55)		-0.086 (-1.16)	0.055 (0.53)
Loss$_{(t-1)}$		-0.405*** (-4.70)	-0.488*** (-4.55)		-0.405*** (-4.71)	-0.488*** (-4.55)
Capex/Assets$_{(t-1)}$		-5.303*** (-5.24)	-0.671 (-0.52)		-5.291*** (-5.23)	-0.639 (-0.50)
R&D/Assets$_{(t-1)}$		2.363*** (4.16)	-1.845 (-1.55)		2.350*** (4.14)	-1.872 (-1.57)
Loan Spread$_{(t-1)}$		-0.169 (-1.63)	-0.102 (-0.76)		-0.170 (-1.64)	-0.107 (-0.80)
YEAR EFFECTS	YES	YES	YES	YES	YES	YES
INDUSTRY (FF 48) EFFECTS	YES	YES	NO	YES	YES	NO
COUNTRY EFFECTS	YES	YES	NO	YES	YES	NO
FIRM EFFECTS	NO	NO	YES	NO	NO	YES
NUMBER OF OBSERVATIONS	39,009	39,009	12,227	39,009	39,009	12,227

As discussed above, we expect this correlation to be even stronger for firms exhibiting financial flexibility. To examine this idea, we re-estimate Specifications 1.A –1.C, however, allowing leverage (as a proxy for financial flexibility) to moderate the relation between RI and TMA activity. The results are reported in Specification 2.A–2.C. Consistent with intuition, the coefficient for RI increases in size, and the coefficient for the interaction term is statistically significant and negative. Indeed, the baseline coefficients actually double in size, suggesting that increasing RI by one standard deviation increases the odds of engaging in TMA in the next period by 12 percentage points for zero-leverage firms from 6% to 18%.

3.2 Consequence analysis

3.2.1 Empirical approach

To study the consequences of TMA activity for RI, we re-arrange the dataset. Specifically, we create a panel-data set, where "deals" are the subject of analysis and the time variable is defined as "calendar year of the deal". In other words, we switch the time dimension to event-time relative to the event-year (t=0). Thereby, we only keep the years t −2, t −1, 0, t+1, t+2.

Using this data, we then regress a firm's RI on the corresponding event-years and a set of controls:

$$RI_{it} = a_0 + \beta_1 year_{(t-2)} + \beta_2 year_{(t-1)} + \beta_3 year_{(t+1)} + \beta_4 year_{(t+2)} + \sum \beta_{(5,i)} X_{(i,t-1)} + \beta_6 \vartheta_i + \beta_7 \varphi_t + \varepsilon_{it}, \quad (3)$$

where the choice of lagged control variables ($X_{i,t-1}$) is based on Lee et al. (2018) and extended by further determinants of RI (cash flow, cash flow volatility, cash holdings, tangibility, closely held shares) and other deal- and country-related controls (deal experience and GDP-per capita), all defined in Table 7. The variable ϑ_i includes deal fixed effects to control for time invariant deal-specific factors.

3.2.2 Baseline results

Table 4 reports our baseline results with regard to consequences of TMA activity. While Specification 1 allows for firm and country characteristics, as well as deal fixed effects, Specification 2 also allows for calendar year effects.

Two results stand out. First, we do not find significant coefficients for the pre-event periods ($year_{t-2}$ and $year_{t-1}$) relative to the year of the acquisition (t=0). Second, we find a positive significant coefficient of 0.07–0.08 in year two after the deal ($year_{t+2}$). Specifically, the coefficient of 0.072 for $year_{t+2}$ in Specification 2 represents approximately 60% of the mean RI (0.12), suggesting economic importance.

Table 4: Consequence analysis – baseline results

Notes: This table presents the results of OLS regressions of the event-year dependent effect of TMA activity on RI relative to the event-year (t=0). Specification 1 presents the baseline results and includes deal fixed effects and a set of control variables as described in section 3.2.1. Specification 2 expands the model by adding year fixed effects. In all regression specifications, real option intensity is used as the dependent variable. All non-dichotomous firm-level variables are winsorized by year at the 1% and 99% threshold to mitigate concerns of outliers. All independent variables are lagged by one period. All variables are defined in Table 7. The t-statistics in parentheses are based on robust standard errors, clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

SPECIFICATION	1	2
SAMPLE	TMA OF NON-TECH FIRMS	TMA OF NON-TECH FIRMS
DEPENDENT VARIABLE	REAL OPTION INTENSITY	REAL OPTION INTENSITY
METHOD	OLS	OLS
Eventyear t–2	-0.024 (-0.81)	-0.019 (-0.54)
Eventyear t–1	0.022 (0.99)	0.016 (0.67)
Eventyear t+1	0.040* (1.75)	0.037 (1.44)
Eventyear t+2	0.077** (2.50)	0.072** (2.01)
CONTROLS	YES	YES
DEAL EFFECTS	YES	YES
YEAR EFFECTS	NO	YES
-NUMBER OF OBSERVATIONS	12,731	12,731
NUMBER OF DEALS	3,263	3,263
R-SQUARED	0.050	0.086

3.2.3 Cross-sectional heterogeneity

We argue that the increase in RI of non-tech firms pursuing TMA is based on the newly acquired options to grow. Consequently, we expect that the effect is relatively stronger for firms that benefit more from the acquired options. Hence, we examine cross-sectional variation for small firms (e.g., Grimpe and Hussinger 2008) with a comparably lower level of RI. Additionally, we investigate less diversified firms (more focused firms) in terms of product segmentation, which limits options for growth.

To test this conjecture, we expand equation (3) with interaction-effects between small (focused) firms and the corresponding event-year. Table 5 reports the results of this exercise.[17] In line with expectations, we find a positive significant interaction term between small firms and event-year t+2 ($year_{t+2}$ *CSH) in both specifications. Moreover, the size of the interaction term is impressive, suggesting that the correlation triples for small and focused firms.

17 We classify a firm as small in the case that firm size is within the bottom three deciles in event-year t–2. We define a firm as focused if the number of product segments is within the bottom three deciles in a given country in event-year t–2. The classification is based on the event-year t–2 to mitigate the concern of a deal-effect on the corresponding classification.

Table 5: Consequence analysis – cross-sectional heterogeneity

Notes: This table presents the results of cross-sectional heterogeneity of small and more focused firms. Specifically, we expand the specifications from Table 4 by adding interaction terms between the corresponding event-year and the characteristic small firm (1) and more focused firm (2). In all regression specifications, real option intensity is used as the dependent variable. All non-dichotomous firm level variables are winsorized by year at the 1% and 99% threshold to mitigate concerns of outliers. All independent variables are lagged by one period. All variables are defined in Table 7. The t-statistics in parentheses are based on robust standard errors, clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

SPECIFICATION	1	2
SAMPLE	TMA OF NON-TECH FIRMS	TMA OF NON-TECH FIRMS
DEPENDENT VARIABLE	REAL OPTION INTENSITY	REAL OPTION INTENSITY
METHOD	OLS	OLS
CSH	SMALL FIRMS	FOCUSED FIRMS
Eventyear t–2	-0.035 (-0.85)	-0.024 (-0.59)
Eventyear t–1	0.008 (0.26)	0.019 (0.68)
Eventyear t+1	0.052* (1.70)	0.040 (1.38)
Eventyear t+2	0.066* (1.74)	0.077** (2.10)
Eventyear t–2 x CSH	0.012 (0.23)	-0.007 (-0.09)
Eventyear t–1 x CSH	0.046 (1.00)	0.052 (0.71)
Eventyear t+1 x CSH	-0.006 (-0.11)	0.057 (0.81)
Eventyear t+2 x CSH	0.124** (2.05)	0.161** (1.99)
CONTROLS	YES	YES
DEAL EFFECTS	YES	YES
YEAR EFFECTS	YES	YES
NUMBER OF OBSERVATIONS	10.339	10.339
NUMBER OF DEALS	2.310	2.310
R-SQUARED	0.090	0,090

3.3 Robustness of results

3.3.1 Alternative deal-level explanations

Arguably, the significant positive effect of TMA on RI could also stem from non-technology-related deal characteristics. Accounting for this concern, we perform horse-race regressions, controlling for four common deal characteristics from the related literature (e.g., Aybar and Ficici 2009; Martynova and Renneboog 2011). Specifically, in the four specifications reported in Table B1, we separately control for (i) cross-border deals, (ii) private targets, (iii) cash deals, and (iv) deal value disclosures. The results remain unchanged.

3.3.2 Heterogeneity in RI

Our findings may be prone to structural differences in RI of firms pursuing TMA and hence are subject to a sample selection bias. To address this concern, we match non-TMA to our sample of

TMA with similar RI characteristics in advance of the deals. Matching is based on industry affiliation, RI, RI-growth, and a battery of further variables potentially correlated with RI.[18] For the analysis, we introduce an interaction term between non-TMA and the corresponding event-year capturing the non-TMA differential effect. In case TMA creates significantly higher RI than non-TMA with a similar pre-deal RI, we should observe no significant difference between the two types of deals in advance of the event ($year_{t-1}$; $year_{t-2}$), consistent with the parallel trend assumption (e.g., Wei et al. 2020), and a significant positive coefficient in the post-event-years. Consistently, we find in Table 6, Specification 1 a significant positive coefficient of 0.093 for the base effect in, $year_{t+2}$ referring to TMA and a significant negative coefficient of -0.062 for $year_{t+2}$ * *Counterpart*, implying that non-TMA show a significantly smaller effect on RI, alleviating concerns of sample selection bias.

3.3.3 TMA as a choice variable

Considering that TMA activity is a variable of choice, it might be argued that the identified RI-effect is not driven by TMA but by another (omitted) variable, which is positively correlated with both the decision to pursue a TMA and RI (e.g., Martynova and Renneboog, 2011). We face this concern by forming a second matched sample, integrating withdrawn TMA.[19] This approach allows for the separation of the decision to engage in TMA from the effective outcome. In line with our previous results, the positive TMA effect should only be observable for completed TMA containing the newly acquired real options.

The results in Table 6, Specification 2 further corroborate our previous findings, with a positive significant base effect quantified by a coefficient of 0.229 capturing the implemented TMA, and a significant negative effect for the withdrawn TMA ($year_{t+2}$ **Counterpart*) of -0.256. As we do not expect to find any effect on RI for withdrawn TMA, we apply a test of difference in coefficients from zero ($\lambda_1 + \lambda_2 = 0$). As expected, we cannot reject the null of a significant difference from zero for firms with withdrawn TMA (p-value 0.873).

18 The matching variables are Industry affiliation (following the 10 industry portfolios by Eugene Fama and Kenneth R. French), RI, RI-Growth, Firm Size, Book-to-Market, Leverage, Trading Volume, Firm Age, Tangibility, and Deal Experience. The matching procedure is based on event-year t–1 using nearest neighbor matching without replacement. The match is conducted in event-year t–1 to maximize similarity in the event-year. In order to control for distances of matched pairs, we apply a caliper restriction of 0.001.

19 We classify a TMA as withdrawn, in case we find a “withdrawn date” provided by the SDC-database. The matching procedure is conducted as in 3.3.2

Table 6: Matched sample regressions

Notes: This table provides results for matched sample analyses. Specification 1 provides the results for matching non-TMA to the sample of TMA based on the following matching variables: Industry affiliation (FF 10), RI, RI-Growth, Firm Size, Book-to-Market, Leverage, Trading Volume, Firm Age, Tangibility, and Deal Experience (matching period event-year t-1; nearest neighbor matching without replacement). We apply the Fama-French 10 industry definition to trade off the number of matched pairs. The match is conducted in event-year t-1 to maximize similarity in the event-year. In order to control for distances of matched pairs, we apply a caliper restriction of 0.001. In all regression specifications, real option intensity is used as the dependent variable. All non-dichotomous firm-level variables are winsorized by year at the 1% and 99% threshold to mitigate concerns of outliers. All independent variables are lagged by one period. All variables are defined in Table 7. The t-statistics in parentheses are based on robust standard errors clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

SPECIFICATION	1		2
SAMPLE	MATCHED SAMPLE		MATCHED SAMPLE
DEPENDENT VARIABLE	REAL OPTION INTENSITY		REAL OPTION INTENSITY
METHOD	OLS		OLS
MATCHING APPROACH	MATCHING OF NON-TECH MOTIVATED DEALS TO TECH-MOTIVATED DEALS	*COEFFICIENT*	MATCHING OF COMPLETED TECH-MOTIVATED DEALS TO ANNOUNCED BUT WITHDRAWN TECH-MOTIVATED DEALS
Eventyear t-2	-0.021 (-0.58)		-0.070 (-0.43)
Eventyear t-1	0.017 (0.67)		-0.116 (-0.94)
Eventyear t+1	0.050* (1.95)		0.022 (0.20)
Eventyear t+2	0.093*** (2.68)	Λ_1	0.229* (1.82)
Eventyear t-2 x Counterpart	-0.022 (-0.86)		-0.092 (-0.81)
Eventyear t-1 x Counterpart	-0.008 (-0.35)		-0.052 (-0.41)
Eventyear t+1 x Counterpart	-0.045* (-1.88)		-0.095 (-0.80)
Eventyear t+2 x Counterpart	-0.062** (-2.19)	Λ_2	-0.256** (-2.19)
Difference		H_0: $\Lambda_1 + \Lambda_2 = 0$	*p = 0.873*
CONTROLS	YES		YES
DEAL EFFECTS	YES		YES
YEAR EFFECTS	YES		YES
NUMBER OF OBSERVATIONS	21,770		484
NUMBER OF DEALS	4,820		106
R-SQUARED	0.091		0.244

4 Summary and conclusions

This study empirically examines "access to technology" acquisitions, which we call technology-motivated acquisitions, and the role of real options in the acquisition behavior of European non-tech firms. Analyzing 39,009 M&A transactions by listed European firms over the period 2001–2020, we find that non-tech firms actively managing their real option portfolios are more likely to engage in technology-motivated acquisitions. Furthermore, our findings indicate that such acquisitions lead to an increase in firms' real option intensity. These results are robust across several sensitivity tests.

Our study has important managerial implications. *First*, non-tech firms can enhance their real option intensity (RI) by investing in technology-driven business models outside their core business areas. Notably, this positive effect typically outweighs potential challenges related to post-merger integration of acquired technologies. Our findings are consistent with a "transformational role" view of technology-motivated acquisitions, where non-tech firms leveraging active RI management can further strengthen their real option intensity through these deals. To realize this potential, non-tech firms should re-think their capital allocation process. Specifically, it is important to not only feed the existing businesses, but also invest in – from the perspective of the non-tech firm – "unexplored territory". However, to be successful in this endeavor, the firm must develop organizational capabilities that enable them to:

(i) systematically monitor technological trends and advancements,
(ii) adapt their strategic direction in response to such developments,
(iii) proactively identify and evaluate market opportunities,
(iv) effectively negotiate with target firms that may have distinct corporate cultures, and
(v) successfully close these deals and integrate the targets to align with their corporate strategy.

Second, firms seeking to access externally developed technology through technology-motivated acquisitions should carefully manage their capital structure. Research by McConnell and Servaes (1995) highlights a negative relationship between leverage and firm value for growth-oriented firms. Similarly, our findings show that high leverage (a) reduces the likelihood of engaging in technology-motivated acquisitions and (b) weakens the positive relationship between a firm's real option portfolio and its propensity to pursue such acquisitions. These results underscore the importance of maintaining financial flexibility to enable firms to undertake transformational strategies effectively (Fischer et al., 2024).

Third, the dictionary developed in this study offers a practical tool for both practitioners and researchers to identify technology-motivated acquisitions. By adopting a holistic perspective, the dictionary consolidates insights from (i) academic literature, (ii) publicly available technology-related lists, and (iii) practitioner input, making it a valuable resource for facilitating target identification.

Lastly it is essential to acknowledge the limitations of the textual analysis approach used in this study. First, the dictionary employed is inherently idiosyncratic. Since it forms the basis for deal classification, alternative dictionaries may yield different classifications and potentially different results. Second, our analysis relies on deal summaries provided by the data source used in this study (Refinitiv, now part of LSEG). Future research could extend this approach by incorporating other sources of information, such as corporate announcements, earnings calls, analyst reports, or media coverage, to improve deal classification and analysis.

Table 7: Variable definitions

Notes: This table provides definitions for variables on firm-level (Panel A), deal-level (Panel B) and country-level (Panel C). Firm level and deal level data is downloaded from Refinitiv. Country level data is drawn from OECD, World Bank, and the European Central Bank

VARIABLES	DEFINITION
Panel A: Firm level variables	
Real Option Intensity (RI)	Defined as in Lee et al. (2018), real option intensity (β) represents the sensitivity of stock returns to changes in stock return volatility based on the following equation: $r_{(i,t)} - r_{(f,t)} = a_t + \beta \Delta Volatility_{(i,t)} + \gamma \eta_{(i,t)} + \sum \delta X_{(i,t)} + \varepsilon_{(i,t)}$, with $r_{(i,t)} - r_{(f,t)}$ defined as weekly excess return, $\Delta Volatility_{(i,t)}$ as the difference in standard deviation of daily stock returns between week t and week t–1 for firm i. The term $\eta_{(i,t)}$ represents the market factor loading estimated with daily information in a given month for firm i and $X_{(i,t)}$ as a vector of firm characteristics known at the beginning of a given week for firm i, which include: ln(1+Book Equity/ Market Equity), ln(1+Market Equity), six week lagged return, and weekly trading volume per number of shares.
$\text{Size}_{(t-1)}$	Logarithm of (1+ total assets).
$\text{Leverage}_{(t-1)}$	Book value of total debt divided by total assets.
$\text{Cash Flow}_{(t-1)}$	Earnings after interests, dividends, and taxes before depreciation divided by total assets.
$\text{Tobin´s Q}_{(t-1)}$	Market value of assets divided by the book value of assets. The market value of assets is defined as the book value of assets minus the book value of equity plus the market value of equity.
$\text{Payout}_{(t-1)}$	Dummy variable equal to one if the firm pays dividends in the corresponding period.
$\text{Negative Net Income}_{(t-1)}$	Dummy variable equal to one if net income is negative in the corresponding period.
$\text{Capex}_{(t-1)}$	Capital expenditures divided by total assets.
$\text{lnR\&D}_{(t-1)}$	Logarithm of (1+research and development expenses).
$\text{Book-to-Market}_{(t-1)}$	Logarithm of (1+total shareholders’ equity divided by the market value of equity).
$\text{Long Term Leverage}_{(t-1)}$	Long-term debt divided by total assets.
$\text{Diversification}_{(t-1)}$	Logarithm of (1+ number of business segments).
$\text{Trading Volume}_{(t-1)}$	Yearly average trading volume divided by the number of shares.
$\text{Firm Age}_{(t-1)}$	Logarithm of (1+firm age).
$\text{Cash Flow Volatility}_{(t-1)}$	The standard deviation of cash flow calculated as the firm–year standard deviation of cash flow for the previous five years (minimum three years).
$\text{Cash Holdings}_{(t-1)}$	Cash and short-term investments divided by total assets.
$\text{Tangibility}_{(t-1)}$	Net property, plant and equipment divided by total assets.
$\text{Closely Held Shares}_{(t-1)}$	Logarithm of (1+closely held shares).
$\text{Deal Experience}_{(t-1)}$	Moving sum of deals conducted by a firm in the three preceding years.
Panel B: Deal level variables	
M&A Deal	Dummy variable equal to one if the firm engages in an M&A deal.
TMA	Dummy variable equal to one if the firm engages in a TMA deal.
Cross Border Deal	Dummy variable equal to one if the firm performs a cross border M&A deal.
Cash Deal	Dummy variable equal to one if the firm performs a (100%) cash deal.
Private Target	Dummy variable equal to one if the target firm is private.
Deal Value Disclosure	Dummy variable equal to one if the deal value of the corresponding M&A deal is disclosed.
Panel C: Country level variables	
$\text{Loan Spread}_{(t-1)}$	Lending margins for new business loans (from European Central Bank). Missing countries were replaced by available corresponding data from the World Bank. Missing country year observations were replaced by the closest available year observation in the respective country.
$\text{ln(GDP p.c.)}_{(t-3)}$	Logarithm of the gross domestic product in constant 2015 U.S. dollars divided by the total population.

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Appendix 1. Dictionary of tech-terms

Our aim is to identify tech-motivated deals. Therefore, we draw on the method of textual analysis and conduct the deal-classification using a dictionary-based approach. Specifically, we proceed in three main steps. *First*, we construct a dictionary of tech-terms, i.e., dictionary of terms characterizing (emerging) technologies. The dictionary aggregates terms from

- academic literature (Chen and Srinivasan, 2019; Garcia de Lomana et al., 2019; Hanelt et al., 2021; Kindermann et al., 2020),
- publicly available technology related lists (following Bonaccorsi et al., 2020; Joung and Kim, 2017), namely the annual MIT list of *10 Breakthrough Technologies*, Wiki lists on *Emerging Technologies*, Gardner's *Top 10 Strategic Technology Trends*, and Scientific American's *Top 10 emerging technologies,* and
- suggestions from business experts.

Each keyword in the dictionary is transferred to lowercase, word endings are adjusted to allow for multiple word forms, and connotations and other notations are added whenever appropriate. Resulting in a dictionary containing 759 unique keywords which can be allocated to three main categories – *digital, product and process improvement,* and *environment* as provided in the following table.

Second, we construct a *deal summary* for each identified deal. The *deal summary* provides the text to classify the transaction as tech-motivated. Relying on all relevant transaction information disclosed by SCD, we aggregate all textual information contained in in the variables "Target Business Description" and "Deal Synopsis". In addition, we remove company names as a precautionary measure. Any acquirer that includes, i.e., "software" in its company name could potentially lead to misclassification of the deal and is therefore removed.

Third, using the Linguistic Inquiry and Word Count (LIWC) from Pennebaker et al. (2015), we analyze the deal summaries and classify a transaction as a tech-motivated deal in case the summary includes at least one of the tech-related terms from the dictionary of tech-terms.

Appendix A: Dictionary of tech-terms

This table represents all used keywords of our dictionary, grouped into three main categories – digital, product and process improvement, and environment. Double listings between categories can occur. * indicates different ending.

DIGITAL						
3d displa*	autonomous car*	cpp/gmr	expressive augmentation	internet of nanothings	physical internet	social media computing
3-d displa*	autonomous rail rapid transit	crash-proof code	eyetap	internet of things	platform	social robot*
3d optical data storage	autonomous thing	crowdfunding	ferro liquid displa*	internet of things platform	practical blockchain	social tv
3-d optical data storage	autonomous vehicle*	cryptocurrenc*	ferroelectric ram	invisible analytic*	practical quantum computer*	software
3d print*	avoid drone*	cybermethodolog*	field emission displa*	iot	predictive analytic*	software-defined anything
3-d print*	babel-fish earbud	cybersecurity mesh	fjg	laser displa*	programmable metallization cell	software-defined application*
3d xpoint	baxter	data analytic*	flexible displa*	laser video displa*	project loon	software-defined infrastructure*
4g cellular communication*	bayesian machine learning	data as a service	four-dimensional printing	li-fi	qarnot	software-defined networking
5g	bi-directional	data product	free-space displa*	m2m	quantified self	software-defined radio
5g wireless	big data	data-based insurance	gastrobot*	maas	quantum computer*	sonos
5g cellular communication*	biometric*	deep learning	general purpose computing	machine augmented cognition	quantum computing	spatial computing
6g cellular communication*	bionic contact lens*	device mesh	general-purpose computing	machine to machine	quantum dot	speech recognition
actionable analytic*	blockchain	differential privacy	gestural interface*	machine translation	quantum dot displa*	stasis chamber*
adaptive security architecture	body-adapted wearable electronic*	diffusion tensor imaging	gesture recognition	machine vision	racetrack memory	strategic big data
advanced analytic*	botnets of things	digital	google glass*	magic leap	reality mining	subvocal recognition
advanced food tracking	bpm	digital ethic*	gyrnoid	magnetoresistive random-access memory	real-time search	surface-conduction electron-emitter display
advanced machine learning	brain-computer interface*	digital genome	hamr	mamr	reinforcement learning	swarm robotic*
advanced system architecture	brain-reading	digital imaging	hi mems	mesh app	robot dexterity	taas
agricultural drone*	business analytics	digital medicine	high altitude platform*	micro mobility	robotic surgery	tdmr
agricultural robot*	business intelligence	digital money	high energy density power system*	millipede memory	robotic*	telescopic pixel displa*
agricultural robotic*	capable digital helper	digital privacy	holograph*	mobile 3-d	rram	temporary social media
ai	car-to-car communication*	digital scent technology	holographic data storage	mobile app*	scooter-sharing system	tesla autopilot
ai engineering	cbram	digital technology platform	home energy system	mobile collaboration	screenless displa*	tiny ai
ai foundation	cell-phone virus	digital twin*	hosted virtual desktop	mobile device	self driving system*	t-ram
ai security	civic technolog*	distributed cloud	html5	mobility on demand	self-driving car*	ttram
ai-discovered molecule	claytronic	distributed ledger technolog*	hybrid cloud	multimodal contactless biometric face system	self-driving truck*	ubiquitous computing

ai-driven development	client architecture	distributed storage	hyperautomation*	multimodal contactless biometric iris system	self-reconfiguring modular robot*	ultraprivate smartphone*
ai-led molecular design	client computing	dna app store	immersive virtual reality	multi-primary color displa*	semantic web	unhackable internet
airborne network	cloud architecture	dna data storage	in memory computing	natural language processing	sense and avoid drone*	universal authentication
ambient intelligence	cloud computing	dna digital data storage	information oriented software development	neural-sensing headset	serverless computing	vehicle on demand
ambient user experience*	cloud program-ming	driverless car*	intelligent analytic*	nram	skyrmion	virtual appliance
android	cloud streaming	drone displa*	intelligent app	nvsram	smart grid	virtual patient
answer machine*	cloud to the edge	drone*	intelligent apparel	oculus rift	smart machine*	virtual reality
anywhere ope-ration*	computer-generated imagery	dueling neural network	intelligent composable business	oled displa*	smart space*	virtual retinal displa*
apple pay	computing everywhere	e-learning	intelligent software assistant	open ai ecosystem	smart speaker	volumetric displa*
artificial general intelligence	connected service	emergent artificial intelligence	intelligent thing	optical computing	smart transformer	wearable computer
artificial intelligence	continuous adaptive risk	emerging magnetic data storage technolog*	interferometric modulator displa*	personal cloud	smart watch*	web app*
augumented analytic*	continuous adaptive trust	empowered edge	internet of behavior	pervasive analytic*	smart wind	web-scale it
augumented reality	conversational interface*	e-textile	internet of behaviour	pervasive wireless	smarter fertilizer	wireless communication
automation	conversational platform*	event driven	internet of dna	phase-change memory	smooth-talking ai assistant*	x-ray communication
autonomous agent	conversational system*	exascale computing	internet of everything	photonic computing	smr	z-ram
PRODUCT AND PROCESS IMPROVEMENT						
$100 genome	carbon nanotube field-effect transistor	fullerene	lightweight small arms technology program	nanowire lithium-ion batter*	quantum computing	stretchable silicon
2d material*	caseless ammunition	fusion rocket	liquid batter*	nantenna	quantum cryptograph*	superalloy
2-d material*	cbram	galileo	liquid biopsies	navigation doppler lidar	quantum dot	supercharged photosynthesis
3d displa*	cellulolytic enzyme	gastrobot*	liquid biopsy	neuroinformatic*	quantum dot displa*	supergrid*
3-d displa*	charging infrastructure	gene drive	lithium iron phosphate batter*	neuromorphic chip	quantum radar	super-plastic alloy
3d metal print*	charging service	gene editing	lithium-air batter*	neuromorphic engineering	quantum sensing	supersonic transport*
3-d metal print*	circula economy	gene therapy 2.0	lithium-ion batter*	neuromorphic technolog*	quantum supre-macy	surface-conduction electron-emitter display
3d print*	circular material usage	generation iv reactor	lithium-sulfur batter*	neuron control	quantum wire	suspended animation*
3-d print*	cloak of invisibility	genetic engineering	litracon	neuronal-sensing headset	racetrack memor*	synthetic biolog*
3d printing material	cloaking device	genetic fortune-telling	logistics on demand	neuroprosthetic*	racetrack memory	synthetic cell*
3-d printing material	cognitive radio	genetically modified food	lower- carbon cement	new-wave nuclear power	radio-frequency identification	synthetic diamond
3d transistor	collaboration technolog*	genome editing	m2m	next gerneration batter*	reality mining	synthetic genomic*
3-d transistor	collaborative telepresence	genomic vaccine*	maas	next-generation robotic*	regenerative medicine	systems metabolic engineering
3d xpoint	comparative interactomic	global navigation satellite system	maglev train	non-rocket spacelaunch	remanufacturing	tdmr

adaptive compliant wing*	conductive polymer*	graphene	magnesium batter*	nootropic	remote manufacturing	telescoped ammunition
additive manufacturing	connectomic*	graphene transistor	magnetic levitation	nram	remote sensing	telescopic pixel displa*
advanced food packaging	construction 3d print*	graphic processing unit*	magnetic nanoparticle	nuclear launch cannon	resveratrol	temporary social media
aerogel	context-rich system*	gravity batter*	magnetic refrigeration	nuclear photonic rocket*	reusable launch system*	thermal copper pillar bump
aeroscraft	counterparty technolog*	ground effect train	magnetic-resonance force microscopy	nuclear pulse propulsion	reusable rocket	thick-film dielectric electroluminescent technolog*
agile robot*	cpp/gmr	gynoid	magnetoresistive random-access memory	nuclear reprogramming	reversing paralysis	three-dimensional integrated circuit
agricultural drone*	crower six stroke engine*	gyrnoid	magnetorheological fluid*	nuclear fusion power	risk-based securit*	time crystal
agricultural robot*	cryogenic treatment	ha batter*	magnonic	nvsram	risk-based self-protection	time-multiplexed optical shutter
agricultural robotic*	cryonic	hamr	mahem	offline web application*	rna-based therapeutic*	tiny ai
airborne laser	cryoprotectant	hashcache	male contraception	oled	rnai interference	tissue engineering
airless tire	cultured meat	head transplant	mamr	oled displa*	robot dexterity	traceabilit*
alcubierre drive	custom cancer vaccine	hi mems	mass driver	olev	robotic surgery	t-ram
americium batter*	de-extinction	hibernation animation*	material quantum leap	omni processor	robotic*	trans-cranial neural characterisation
amorphous metal	democratization	high-speed material discover*	meat incubator	oncolytic virus	rram	trans-cranial neural characterization
ampakine	directed energy weapon	high-temperature superconductivity	megascaledesalination*	online electric vehicle*	safer nuclear reactor	trans-cranial neural sensing
answer machine*	disordered protein*	high-temperature superfluidity	memory implant*	optical transistor	satellite mega-constellation	translucent concrete
anti-aging drug*	distributed manufacturing	homomorphic encryption	memristor	optogenetic*	scramjet	traveling-wave reactor
anti-gravity	distributed storage	hoverbike	metabolic engineering	orbital rocket	sds	t-ray
antimatter weapon*	domed city	hovertrain	metabolomic*	organic electronic*	sds kit	tricorder
arcology	driverless car*	human augmentation	metal foam	organic light-emitting diode	sector coupling	ttram
artificial brain	drone displa*	human cell atlas	metal insulator metal chip	organic light-emitting transistor	sector storage	tweel
artificial embryo*	drone*	human dna vaccination	metamaterial cloaking	organs-on-chip*	self-healing material*	twistronic*
artificial gravity	dual-action antibod*	human microbiome therapeutic*	metamaterial*	orion nuclear starship	senolytic*	ultra high definition television
artificial intelligence	dynamic armor	hvd	micro air vehicle*	paper diagnostic*	sense and avoid drone*	ultracapacitor*
artificial photosynthesis	egg stem cell*	hybrid forensic*	microfluidic optical fiber	particle beam weapon*	sense drone*	ultra-high-definition television
artificial uterus	electric double-layer capacitor	hydrogen economy	microfluidic*	particle-beam weapon*	sensing city	universal authentication
asteroid mining	electro hydrodynamic propulsion	hyperautomation*	microneedle*	personal aircraft	separating chromosome*	universal memory
atmospheric carbon dioxide removal	electroceutical	hypercapacitor	microscale 3-d printing	personal rapid transit	service architecture*	universal translation
atomic magnetometer	electroencephalograph*	hypereutectic alloy	millipede memory	personalised medicine	silicene	unmanned vehicle*
atomtronic	electrolaser	hyperloop*	mim chip	personalized medicine	silicon photonic*	utility fog
automatic visual insepction of aircraft	electromagnetic weapon	hyper-personalized medicine	miniaturized satellite	phage therap*	silicon–air batter*	vactrain

automation	electronic nose	hypersonic cruise missile	mobility solution*	phase-change memory	single-cell analysis	vehicle on demand
autonomous agent	electronic textile*	hypertelescope	modeling surprise	phased array optic*	skyrmion	vehicular communication system
autonomous car*	electrothermal-chemical technolog*	immersive experience	molecular assembler	phased-array optic*	slack	vertical farming
autonomous rail rapid transit	emerging magnetic data storage technolog*	immune engineering	molecular electronic*	photon rocket	smr	vertical landing
autonomous thing	engineered negligible senescence	immuno oncology	molecular nanotechnolog*	photonic laser thruster	social commerce	vertical take-off
autonomous vehicle*	engineered stem cell*	immunotherap*	molten salt batter*	picotechnolog*	social indexing	vertical take-off and landing
avoid drone*	enhanced education technolog*	implantable drug-making cell*	molten salt reactor	plantibod*	social robot*	virotherap*
backpack helicopter	enzybiotic*	implantabl electronic*	multi function structure*	plasma propulsion engine*	social tv	virtual retinal displa*
bacterial factor*	epigenetic*	in memory computing	multiexperience*	plasma weapon	solarcity's gigafactor*	vitrification*
battery swapping	e-textile	in vitro meat	multimodal contactless biometric face system	plasmonic material*	solid-state batter*	volumetric displa*
baxter	exocortex	inflatable space habitat	multimodal contactless biometric iris system	power grid control	solid-state drive	vortex engine
bead washing machine	exocortice	interferometric modulator displa*	multi-primary color displa*	powered exoskeleton	solid-state transformer	vortex ring gun
beam-powered propulsion	femtotechnolog*	invisible revolution	nano-architecture	precise genetic engineering technique*	sonic weapon*	v-tex
bi-directional	ferro liquid displa*	ion drive	nanobiomechanic*	precise genetic-engineering technique*	sonogenetic*	vtol
biomechatronic*	ferroelectric ram	ion thruster	nanoelectromechanical system*	precision agriculture	sonos	web app*
biosomatic cellular engineering	field emission displa*	isolated brain	nanofiber	precision-guided firearm	space elevator	web-scale it
biotechnolog*	fjg	jet pack	nanohealing	precooled jet engine*	space fountain	whole-genome synthesis
body implant*	flexible electronic*	lab-grown meat	nanomaterial*	predicting preemie	space gun	wireless communication
bpm	flexible wing*	lab-on-a-chip	nanomedicine	prenatal dna sequencing	spaceplane*	wireless energy transfer
brain mapping	float to orbit	laser displa*	nanopiezo-electronic*	presicion farming	special purpose vehicle *	wireless long-range electric shock weapon
brain organoid	fluidic flight control	laser video displa*	nanopore sequencing	privacy-enhancing computation	spintronic*	witricit*
brain-computer interface*	flying car*	laser weapon	nanoradio	probabilistic chip	spv	x-53 active aeroelastic wing*
cancer genomic	force field	launch loop	nanorobotic*	programmable matter	srt1720	z-ram
carbon management	four-dimensional printing	led lamp	nanoscale engineering	programmable metallization cell	starchip*	
carbon dioxide catcher	fourth-generation optical disc*	life extension	nanosensor*	propellant depot	starshot*	
carbon dioxide compensation	fourth-generation reactor*	lightcraft*	nanostructured carbon composite	prosthesis	stasis chamber*	

carbon dioxide conversion	free-space displa*	light-field photography	nanowire	pulse detonation engine	stealth technolog*	
carbon nanotube	full genome sequencing	light-trapping photovoltaic*	nanowire batter*	pure fusion weapon	stem cell treatment	
ENVIRONMENT						
airborne wind turbine	climate change attribution	e-fuel*	fuel-cell vehicle*	home fuel cell	solar fuel*	ultra-efficient solar
alternative fuel vehicle*	closed ecological system*	electric aviation	fusion power	hot solar cell	solar microgrid*	wireless power
bio fuel*	co2 compensation	electric car*	green bullet*	nanocharging solar	solar power	zero-carbon natural gas
biofuel*	co2 conversion	energy harvesting	green concrete	ocean thermal energy conversion	solar roadway	zero-energy building
biological machine	concentrated solar power	energy-efficient water purification	green energy	perovskite solar cell*	solar sail	
biomechatronic*	csp concentrated solar power	enviromatic*	green hydrogen	photovoltaic*	solar gravitational lens	
bioplastic*	cst concentrated solar thermal	environmental design	grid energy storage	recyclable thermoset plastic*	space-based solar power	
bio-print*	decarbonisation	flywheel energy storage	grid-scale electricity storage	recycling	sun-powered chemistr*	
biotechnolog*	efuel*	fuel cell vehicle*	home energy system	smart wind	thorium fuel cycle	