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Are M&As spurring or stifling innovation? Evidence from antidiabetic drug development*

Jan Malek†, Jo Seldeslachts‡, Reinhilde Veugelers§

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Abstract

This paper provides empirical evidence on which M&A deals spur innovation, and which stifle it. To do so, we consider not only the product market position of the acquiring firm, but also the position of both target and acquirer in the technology space. Focusing on the antidiabetic drugs market, our dataset tracks the lifecycle and patenting of all individual antidiabetic projects in development between 1997 and 2017. We show that most terminations of acquired projects occur while the projects are still far from product market entry. Nevertheless, a number of these early-stage acquisitions have a positive impact on innovation. These cases arise when incumbents acquire projects close to their own projects in product markets, but only if these projects are also close in technology markets. Those deals are associated with increased subsequent patenting, which is consistent with the exploitation of technological synergies. Our results point to the crucial role of combining both product market and technology market positions in assessing the innovation effects of pharmaceutical M&As.

Keywords: M&As, innovation, R&D, pharmaceutics, technology, novelty, patents
JEL Codes: L41, L65, O31

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1 Introduction

The "superstar firm" phenomenon has recently become highly discussed and documented (Autor et al., 2020). For the US economy, for example, De Loecker et al. (2020) show a reallocation of economic activity from low-mark-up firms to high-mark-up firms. In this context, the same study documents that global M&A activity increased more than tenfold between 1985 and 2016, while the aggregate markup increased by about thirty percentage points, suggesting that firms with initially high market power become larger and more powerful through acquisitions. These trends of higher concentration, rising markups and increasing M&A activities are particularly noticeable in industries where technological change and innovation are most intense (Diez et al., 2018), raising concerns on the impact of M&As on innovation dynamics.

Among others, two of the largest jurisdictions, the US and the EU competition authorities have adapted their merger guidelines to take into account innovation dynamics.[1] These jurisdictions include as critical new elements "potential competitors" or "nascent competitors" around deals where large incumbents acquire small, promising targets to control future competition. In the past, these deals have flown under the radar of competition authorities because the targets were often too small in revenues or had no revenues if their products were still in the R&D stage.

A study by Cunningham et al. (2021) coincides with policymakers' new thinking about mergers. Their paper finds that, for the pharmaceutical industry, an incumbent - i.e., a company that has already launched a drug - when acquiring projects, has a higher likelihood of terminating potentially future competing projects in development. So-called "killer acquisitions" comprise about 5%-7% of the M&As in their sample. Some earlier empirical research on acquisitions in pharmaceutical markets reached similar (negative) conclusions. Ornaghi (2009) finds merged pharmaceutical companies to have, on average, a worse innovation performance than the control group of non-merging pharma firms. Haucap et al. (2019) observe that not only average patenting and R&D of the merged entity declines in post-merger periods but also of its rivals. Comanor and Scherer (2012) provide descriptive evidence for a decline in innovation due to acquisitions by the largest

[1] https://www.reuters.com/legal/transactional/back-drawing-board-ftc-doj-rethink-merger-guidelines-2022-03-07/ and http://competitionlawblog.kluwercompetitionlaw.com/2021/04/01/eu-commission-launches- major-merger-control-reform/

pharma companies. Ornaghi and Cassi (2023) find that in a large sample of pharma M&As, post-M&A, inventors are more likely to leave the target company to either exit the industry or to relocate to another company. These exits lead to fewer patents and thus less innovation.

However, while an acquirer's product market position and possible concerns on killing motives for acquisitions have been rightly on the competition policy radar, many M&As, particularly those in high tech environments, also evolve around strategies for obtaining new technological resources or reaping technological benefits from combining technological know-how. Whether acquisitions spur or stifle innovation will depend on the characteristics of the acquirer and the target not only in the product markets but also in the technology markets. Missing the technology side runs the risk of erroneous assessments of the overall net social benefits of M&As (Veugelers, 2012).

While the above-cited papers and the related competition literature on the topic show how positions in product markets can be defined, they are typically less precise in characterizing the technology dimensions. Cunningham et al. (2021) focus on product markets, characterized by the precisely defined "Mechanism of Action" (MoA) of drugs, but do not consider technology markets in detail. Other research on M&As and innovation in pharma markets measures innovation using simple (citation-weighted) patent counts and defines technology positions at the firm level by using patent classes (e.g., Berger et al., 2025; Ornaghi, 2009; Haucap et al., 2019). However, these empirical studies are typically at the firm level and remain thin on assessing technology characteristics of the projects involved in M&A deals, as also virtually all other empirical studies investigating the interplay between competition and innovation (see e.g., Bloom et al., 2013, for a cross-industry study, and Marrazo et al., 2024, for a report on European pharmaceutical M&As).

While the competition papers lack a deep dive into technology market positions of acquirers and targets, the technology literature focuses on technology characteristics of the involved parties, based on detailed information on patents, but it is less focused on the technology characteristics of the involved projects, as well as on the product market characteristics (see e.g., Cloodt et al., 2006; Ahuja and Katila, 2001; Frey and Hussinger, 2011).[2]

We argue that studies on M&As, competition and innovation can benefit enormously

[2]Morzenti (2022) uses patent text similarity contained in the patents to define close mergers for small firms but does not make a distinction between product and technology markets.

from combining product market and technology market characteristics and from adding more detail on the technology dimension. In particular, we propose a precise characterization of the technology position of individual projects subject to M&As. To that purpose, we match each project to its patents, which allows us to use the information from the patent documents to zoom in on the technology characteristics of projects.

Combining both product and technology market characteristics, this paper studies whether acquisitions spur or stifle innovation, depending on the incumbency and closeness of the acquirer and the target not only in the product markets but also in the technology markets. To explore the relationship between M&A activities and innovation, we focus on the antidiabetics sector, an important and growing therapeutic area within the pharmaceutical industry. We trace 1345 projects developed between 1997 and 2017 and connect them to their R&D milestones and ownership changes. With this dataset at hand, we estimate how different outcomes - a project's termination, progression, and follow-up patenting - change where projects are affected through ownership changes, and this is compared to similar projects that were not involved in M&A transactions. When considering progress or not, we take into account the various stages of development in which projects were subject to an M&A transaction. The detailed structure of our data allows us to analyze not only the impact on the projects that were taken over, but also on antidiabetics projects in the acquirer's portfolio. We can, thus, assess not only the impact on (the projects of) each transacting party separately but also the overall combined effect of a transaction since the effects on target and acquirer can substantially differ (Szuecs, 2014).

To unpack heterogeneity in the effects, our analysis considers an acquirer's product market incumbency, its technology incumbency, and closeness between the acquirer's and target's R&D and product markets. We define product market incumbents as firms with launched drugs in the antidiabetics market, while R&D incumbents are firms with their own pre-existing antidiabetic R&D portfolio. Product market overlap is measured like in Cunningham et al. (2021) through MoA overlap. For the technology side, we characterize the closeness between projects in the technology space based on similarity in text contained in the patents associated with each R&D project, based on methods developed by Cassiman et al. (2004) and Arts et al. (2023).

We find that the effects differ significantly. Acquisitions that occur in the later phases

of clinical development, when development costs are high but failure risks are low, are limited in number, but are less likely to have negative innovation effects, as targets' projects are less likely to be terminated. These late stage transactions mainly involve firms not yet active in antidiabetics, neither in the product market nor in the technology space, indicating a strategic move to enter the antidiabetics product market, as is further documented in Malek et al. (2024) and consistent with the findings of Siebert and Tian (2020).

Most M&A transactions, however, take place when projects are in early R&D development stages, where there is still a high risk of technology failure. For these transactions the acquiring firm's technology incumbency is a crucial factor in determining the effects on progress on innovation. Acquisitions by firms with no prior activity in antidiabetic R&D projects result in adverse outcomes for the target projects. Such projects are significantly more likely to get stuck, with a higher likelihood of termination and a lower likelihood of progress. Additionally, their underlying technology is less likely to be further developed, resulting in fewer follow-on patents.

In contrast, projects acquired by firms with prior activity in antidiabetics' R&D exhibit substantially different outcomes depending on the technology closeness and product market overlap between the acquirer's and target's antidiabetics projects. Positive innovation effects are found in a subset of transactions where acquirers are not only both technology and product market incumbents but where target and acquirer projects are also closely aligned in both technology and product markets. In these M&A deals, the likelihood of termination is significantly lower compared to a no-deal scenario, and this not only for the target's projects but also for the acquirer's projects. Furthermore, the acquirer's and target's projects experience more follow-on patenting than other M&A deals.[3] These findings strongly suggest synergies, where two-way spillovers between the target and the acquirer result in positive innovation effects.[4] The proximity of technology and product markets creates opportunities for positive innovation effects rather than negative motives to eliminate competition. These results hint at technology and product market incumbents engaging into "buy instead of build" type of acquisitions. Rather than

[3]This finding is in line with Valentini (2012), who finds for the US medical devices and photographic equipment industry an overall positive impact of M&As on follow-up patenting. However, that paper does not define technology markets and defines its product market very broad; i.e., based on SIC classification 38.

[4]This finding could partly illustrate the theoretical findings of Bourreau et al. (2024) who conclude that in the absence of synergies and spillovers, a merger is likely to reduce consumer surplus.

killing the projects of the target, these acquirers integrate and leverage acquired projects into their own innovation ecosystem, labeled "reverse killer acquisitions," by Caffarra et al. (2020). We further find that none of the product market incumbents behind these effects are the market leaders in antidiabetics, i.e., firms with a high market share. On the contrary, these effects are driven by other, less dominant incumbent firms.[5]

The rest of this paper is organized as follows. Section 2 provides more details on the research setting and on data sources, including the explanation of the construction of the relevant sample. Section 3 presents the empirical implementation, motivation, and definition of all relevant variables. Section 4 presents the results and several extensions and robustness checks. Section 5 concludes.

2 R&D in the antidiabetics industry - Setting and Data

To study the impact of acquisitions on innovation and how this depends on product and technology market characteristics, this paper focuses on the pharmaceutical sector and within this sector on a single disease, diabetes. Diabetes is a disease caused by the insufficient ability (Diabetes type II) or complete inability (Diabetes type I) of the body to produce insulin, a hormone that regulates glucose levels. The expenditure on antidiabetics amounted to 12% of global healthcare expenditure in 2010 (Zhang et al., 2010). Since then, the size of the market has increased substantially, and industry sources anticipate significant further growth (International Diabetes Federation, 2019). This vast market potential creates strong incentives for companies to develop antidiabetics. Together with changing technological opportunities for treating diabetics, it is an excellent market to study M&As and innovation.

Like for other drugs, the R&D process for antidiabetics occurs at the level of individual projects, which are focused on chemical molecules or biological proteins that the company believes may work in a particular way to treat the disease (e.g., type II diabetes). The latter is called the mechanism of action (MoA) and defines the biochemical process by which the drug produces the desired effect in the body.[6] The MoA is central to R&D de-

[5]This result aligns with the findings of Malek et al (2024), who find that market leaders are, on average, less likely to be engaged in acquisitions in the first place.

[6]For example, a DPP-IV inhibitor is a particular MoA used to treat diabetes. These drugs inhibit the DPP-4 enzyme, thereby stimulating the secretion of insulin. This lowers the levels of glucose in the blood.

velopment, as clinical trials are centered around the drug's mechanism of action, combined with the therapeutic area. MoAs play an important role in the definition of the relevant antitrust markets, as drugs with the same MoA are typically seen as substitutable.

Each project follows a well-defined set of development milestones, including pre-clinical, Phase I, Phase II, and Phase III clinical trials, before receiving approval from the US Federal Drug Administration to enter the market (FDA, 2018). The FDA requires public disclosure of these milestones and corresponding data, allowing for comprehensive tracking of each project's progress. The process is standardized, transparent, and rigorously monitored. This allows us to consistently measure and quantify innovation characteristics over time. Like for many other drugs, developing a new antidiabetics drug is a long, risky and costly process. In our sample, only 4% of projects succeed, taking an average of 14 years from development to approval. Early stages have high failure rates but low costs, with expenses rising sharply during late-stage clinical trials.

Although public information on clinical trials does not directly match patents to projects, it is possible to establish such project-patent links, using the publicly available data in the patent filings and the available project information. Patents are crucial in the pharmaceutical sector, offering exclusivity in exchange for public disclosure of technological details. Patents provide valuable information about the drug's active ingredient, formulation, and method of use, enabling a characterization of the technological innovation of the project. Companies file patents early, often before the start of clinical trials.

2.1 Data sources and data construction

We gather information on patents and development milestones at the project level and match it with (changes in) ownership data. The dataset is based on the Pharmaprojects database from Citeline, which offers a comprehensive list of global R&D activity in the pharmaceutical industry at the project level.[7] As a starting point, we identified 2711 projects related to the treatment of diabetes from 1997 to 2017. However, while the database provides information on drug names and sponsors, it lacks information on some aspects of project development, such as information on project progression. The AACT database provides access to information on every clinical study registered at ClinicalTri-

[7]Pharmaprojects is a commonly used commercial database for studying the pharma sector. For example, Adams and Brantner (2006); Kyle (2007); Blume-Kohout and Sood (2013); Branstetter et al. (2014) and Cunningham et al. (2021) all use the Pharmaprojects data.

als.gov, a global repository of clinical studies.[8] We matched our Pharmaprojects sample with these studies, using string matching on sponsor and drug names. This process allowed us to identify the start and end dates of the phases of each project, allowing us to reconstruct the development histories of 2,378 projects, representing 88% of all projects.[9]

We label ownership changes for each project in our database by identifying the sequence of consecutive owners of each project. To do so, we matched relevant firms with the databases Zephyr and SDC Platinum. Manual checks and additional desktop searches were performed to ensure correctness and completeness.[10] We identify 157 instances of ownership changes, corresponding to 144 unique antidiabetics R&D projects that changed hands.[11]

To identify the technological content of each project, we assigned patents to projects based on their underlying biochemical properties. For each project, we searched for patents filed at the US Patent and Trademark Office (USPTO) between the inception and termination dates of a project. Depending on the information available, we used different techniques to establish patent-project links, i.e., chemical, or protein and nucleotide sequences (see Sampat and Williams, 2019). To increase the matching rate, we further used the natural language methods and data from Arts et al. (2021), based on keywords relating to a projects' MoA. Combined with additional manual checks, we matched patents to 80% of projects in our sample. A detailed description of the algorithm and its results is given in Appendix A and in Malek et al. (2024).

We look at all 144 unique antidiabetics R&D projects that changed ownership ("tar-

[8] Available at https://aact.ctti-clinicaltrials.org/

[9] In cases where complete histories could not be obtained, we imputed the missing data by estimating a log-normal distribution of duration per phase and randomly drawing a project's phase duration from the estimated distribution. For each imputation, we manually checked that the sequence of development milestones is not violated.

[10] We excluded large conglomerate transactions, where one big pharmaceutical company acquires another big pharmacautical company. We excluded such cases since these deals are unlikely to relate specifically to diabetes R&D, and are thus not representative in explaining the general transaction dynamics in antidiabetics. We also checked for all our transactions whether they were explicitly linked to diabetes. For that purpose, we used the following data sources: 1) Refinitiv, (i) Deal synopsis, (ii) Deal purpose, (iii) Target Business Description; 2) Press releases of the acquisitions; and 3) General news on the acquisitions on websites. We searched in those data sources for the words "diabetes" or "insulin." We found that for 118 out of 157 acquired projects those sources explicitly mentioned "diabetes" or "insulin," whereas for the others we cannot be 100% sure that the primary reason for the transaction lies within diabetes. Our results are robust to running our estimations with only the 118 transactions; see also further below.

[11] Since consecutive M&As can affect the same single project, the number of treated observations exceeds the number of unique projects exposed to M&As and yields 157 on the target side and 185 on the acquirer side.

get's" perspective). We also include the antidiabetics R&D portfolio that the acquiring companies owned at the time of the transaction ("acquiror's" perspective); our sample contains 162 acquiror's unique antidiabetics projects. In total, we thus have 306 unique treated projects for our analysis.[12] We know the development stage in which the transaction happened for each project, yielding project-phase observations.

3 Variables and empirical implementation

Our main goal is to test whether changes in ownership affect the successful development of projects and whether such changes depend on technology and product market characteritsics. Leveraging the database described in Section 3.1 and 3.2, we construct variables central to our analysis, and detail our empirical implementation in Sections 3.3 and 3.4.

3.1 Key product and technology market variables

For both product market and technology dimensions affecting the impact of M&As on innovation, we focus on incumbency of the acquirer and the relatedness between the acquirer and target projects in technology and product market characteristics. We focus on those deals where the targets are purely active in R&D (R&D incumbents), without any product market incumbency.

R&D incumbency. The ability of a firm to pursue innovation depends on its existing experience with a given technology, i.e., "R&D incumbency" (Arora et al. 2009; Abrantes-Metz et al. 2004; Adams and Brantner 2003). An acquirer can be expected to be more likely to succeed to develop an acquired project further when it can build on the technology know-how and expertise it has acquired from having worked before in the same technological area. At the same time, R&D incumbents may be reluctant to develop the acquired project further, favoring their own projects, driven by path dependency, the "not-invited-here" syndrome or other strategic motives to control the technology market. We split the acquirers into two exclusive groups: R&D incumbents, i.e., acquirers with

[12] A concrete example illustrating this approach is the acquisition of Kos Pharmaceuticals by Abbott in the first half of 2007. At the time of the acquisition, Abbott had three antidiabetic in-house projects in its portfolio (all in preclinical phase) and acquired one antidiabetics project from Kos Pharmaceuticals (in Phase II). Hence, this transaction brings four observations into our database - three from the acquirer and one from the target.

an existing portfolio of antidiabetic R&D projects when a transaction occurs, and R&D non-incumbents, i.e., acquirers with an empty portfolio of antidiabetic R&D projects.

Product market incumbency. Incumbents have complementary assets, such as capital, production and commercialization capabilities, experience, or brand name, to bring R&D projects to success, thereby more likely to push acquired projects forward (Arora et al. 2009; Andersson and Xiao 2016; Grabowski and Kyle 2008). On the other hand, product market incumbents may be driven by protecting their existing market positions and acquire targets with disruptive R&D projects to "kill" them (Cunningham et al., 2021; Federico et al., 2020). We classify an acquiring firm as a market incumbent if it had at least one launched antidiabetic project at the time of the transaction. In the opposite case, it is classified as a market non-incumbent. Product and technology market incumbency might be correlated but do not need to coincide (Cassiman et al., 2004). By design of our sample, all product market incumbents are R&D incumbents, but R&D incumbents are not necessarily product market incumbents.

Closeness in future product markets. With the notable exception of Cunningham et al. (2021), the literature has predominantly analyzed the role of product market closeness between acquirers and targets at the firm level, and with various degrees of preciseness of product market positioning.[13] However, antitrust markets are not defined at the firm level but at the product level, i.e., project/drug level in the pharmaceutical industry. Our dataset allows us to measure closeness at the project level, where we measure the product market closeness between the projects of the acquirer and target based on their MoA. The MoA of a drug/project is arguably the best way to define the product market space, as launched drugs with the same MoA (in the same therapeutic area) are often regarded as substitutes by patients and physicians, thus defining the relevant product markets.[14] Thus, MoA overlap naturally identifies the competing projects in the (future) product market space (Cunningham et al., 2021). Therefore, we split the treated projects acquired

[13]Examples of a firm-level approach when analyzing M&As in the pharma industry are Meder (2016) who defines product markets based on the Anatomical Therapeutic Chemical (ATC) classification system, Yu et al. (2016) who use a commercial database called Inteleos, Bena and Li (2014) and Bloom et al. (2013) who use Compustat's SIC4 classification, and Hoberg and Phillips (2010) who employ text-based analysis of product descriptions from the Securities Exchange Commission (SEC) Edgar website.

[14]See e.g., case M.9274 - GSK/Pfizer Consumer Healthcare Business, case M.7275 - Novartis/GSK Oncology, case M.8955 - Takeda/Shire where relevant antitrust markets have been defined using the combination of the therapeutic area and a project's MoA. Drugs with different MoAs have distinct efficacy and safety profiles, which are key factors for physicians when prescribing drug (see case M.9461 - Abbvie/Allergan, para 51).

by R&D incumbents into two exclusive groups, depending on whether an acquirer's project shared an MoA with the target's project.[15]

When projects that are close in the (future) product market are brought under the same ownership through an acquisition, several effects may arise depending on the strategic motives and competitive context. On the pro-competitive side, the acquisition of close projects can generate cost efficiencies, for example through eliminating redundant manufacturing or consolidating marketing efforts (Hammoudeh and Nain, 2024). Acquirers may also pursue portfolio diversification strategies, using the acquisition to offer a range of differentiated options. However, project overlap can also result in reduced innovation, especially if the product market is already concentrated. Strategic effects may include project discontinuation or tactics such as soft degradation, where the acquired project is sidelined to protect the incumbent's existing projects being displaced by the former (Cunningham et al., 2021; Bonaime and Wang, 2024).

Technological closeness. Our paper's most novel element, we believe, is complementing product market closeness with a measure of technological closeness between between the acquirer's and the target's projects, based on their patent texts from Arts et al. (2021).[16] Major words in title and abstract from all patents relating to a particular project are pooled and the pair-wise cosine similarity is computed between all possible project pairs in our database, where the cosine similarity lies between zero and one (with zero meaning that two projects are technologically orthogonal, and one that they are technologically identical). We define two projects as technologically close, labeled as "twins" when their cosine value lies in the 95th percentile of the distribution of technological similarity of all observation pairs in our dataset (which cosine cutoff value is 0.16).[17] In other cases, i.e., where the R&D incumbents do not have projects that fall in 95th percentile of similarity with the target, we label the two projects as "sibling."[18] A closer technology overlap between the acquirer and the target project may result in larger opportunities for synergy effects by combining both acquirer and target technological know-how. If the target and

[15]Acquirers that are not R&D incumbents have an empty antidiabetics portfolio before a transaction and, therefore, cannot have an MoA overlap in antidiabetics (i.e., within the same therapeutic area).

[16]Arts et al. (2021) provide standardized keywords from abstract, title, and claims of US-granted patents, capturing the most relevant parts of each patent.

[17]A detailed explanation of the construction of technology variables is given in Appendix C. The distribution of the cosine similarities is shown in figure C1 in Appendix C.

[18]We checked the sensitivity of our results using different cutoff rates and other measures of technological overlap (backward patent citations and IPC classes) and report these regressions in the robustness section (Figures 13 and 14 and Tables D14, D15, D16, and D17 in Appendix D).

the acquirer are active in complementary technological fields, economies of scope together with the generation of synergies should dominate the innovation effects on R&D inputs. Yet, the elimination of common R&D inputs is likely to be observed as far as some duplication exists, the more so when projects are very close (Cassiman et al (2005).

3.2 Key outcome variables

We use the histories of clinical trials and patenting activity to measure how a change of ownership influences the development of M&A-affect projects.

Termination. This binary variable captures whether or not a firm has abandoned developing a project. Since firms do not publish information on intentional terminations (i.e., killing), we proxy termination with a lack of further development activity. We classify a project as terminated if it has (i) not continued in transition to the next phase and (ii) stayed exceptionally long in the project's last observed phase, i.e., when a project's phase duration is beyond the mean plus one standard deviation of a typical phase duration in our sample.[19]

Progress. For each phase, this binary indicator equals one if a project has transitioned into the next development phase by the end of the sample period and equals zero if a project stayed in the same phase.[20]

New patenting. As a further measure of innovation (beyond progress in clinical trials), we look at patents assigned to each project. For projects with an M&A transaction, we define the variable New Patents as a binary indicator that equals one if a project received at least one new patent after the transaction date.[21]

[19]The values are based on the estimated phase distributions of all our progressing projects. The phase-specific distributions and cutoff values are presented in Appendix B in figure B1.

[20]We also used variants of "speed of progression" as the outcome variable where a project scores on "fast progressed" if it progressed into another phase and at the same time did so quicker than the median duration of a phase. We decided against reporting, as the found patterns are similar in direction and significance as with our progress variable, but less robust.

[21]This outcome variable provides a complementary outcome measure to Cunningham et al (2021). Cunningham et al (2021) measure project development activity by relying on "events" that the Pharmaprojects database lists for projects. As markers of development activity, they consider events capturing scientific milestones (compounds identified, mechanisms identified, new chemical structure, new disease, new therapeutic activity, target identified, development continuing) and important steps in the commercialization process (first launches, additional launches, first registrations, additional registrations, names granted, new licensees, new patent applications, orphan drug status granted). We construct our own variables, and, while perhaps more limited in scope, have, therefore, more control over their coding.

3.3 Assessing innovation effects of M&As

To assess the innovation effects of M&As, we employ a simple framework measuring the innovation outcomes of the projects belonging to the respective treatment groups (target/acquirer/all compared to their relevant control groups, where we discuss in detail below the control groups used. The regression equation has the following form:

$$Outcome_{ip} = \beta_{0p} + \beta_{1p} \cdot f(Treated_{ip}) + \beta_{2p} \cdot FE_{ip} + \varepsilon_{ip}, \quad (1)$$

with $p \in A, T, A+T$. Observation i corresponds to a project-phase and p represents the acquirer (A), target (T), or all $(A+T)$ project sets, respectively. As explained above, $Outcome_{ip}$ takes the form of three 0/1 outcomes: Termination, Progress or New Patents. The function $f(.)$ and the corresponding vector of coefficients β_{1p} is the treatment effect. As will be further detailed, $f(.)$ encompasses variables for various cuts of the treated sample, allowing us to study the heterogeneity in treatment along various product and technology market positions of the involved parties.

We employ a series of fixed effects FE to control for non-varying characteristics of the projects that may contaminate the treatment effect. A first set, phase fixed effects, controls for the non-varying differences across the various development phases of the projects, most notably their differences in technology uncertainty and risks of failure. A second set of fixed effects, cohort fixed effects, group together projects initiated around the same time. This controls for time trends, and technological trends. A third set of fixed effects controls for the number of patents of each project, patent fixed effects.[22] This is partly a technical control, as more patents will affect the likelihood of scoring on technology closeness or MoA overlap. In addition, it allows to control for the technology size of the involved parties. The breadth and depth of technological know-how of the parties may affect their stewardship of projects towards success. A patent fixed effect allows better sorting out the impact of incumbency and relatedness. The last set of fixed effects relates to projects' MoA, MoA fixed effects. This allows to control for the distinctive features specific to each group of drugs within the same MoA.[23]

[22] To limit the potential influence of outliers, we have discretized the number of patents. We created four binary variables, grouping projects with 1, 2-4, 5-10, and more than 10 patents. These cutoffs were chosen to guarantee enough observations per group. Results are robust to alternative groupings.

[23] We also experimented with fixed effects for technology classes of the patents (IPCs). These, however, did not yield additional effects over MoA fixed effects, while consuming degrees of freedom. The reported

We employ different assumptions on the error term ϵ_{ip}. First off, as the baseline, we consider ϵ_{ip} to be *i.i.d.* However, projects belonging to the same firm might experience common shocks as decisions are often made at the firm level. For example, a cost shock to a particular firm would affect all projects of that firm and make the error terms of within-firm projects correlated with one another. Therefore, in a robustness check we allow standard errors to be correlated and cluster errors at the firm level. Another plausible source of correlation relates to the projects involved in the same transaction. Indeed, elements specific to the transaction, for example, the financing of the deal, the rationale for the acquisition, or integration plans of the acquirer might affect the error term systematically, resulting in cross-correlation between projects involved in a particular deal (Abadie et al., 2017). We, therefore, also allow for standard errors to be clustered at the transaction level.

The nature of the binary outcomes would warrant the estimation of equation (1) by using logit or probit models. However, due to our sample size and the need to accommodate many fixed effects, we face convergence issues. Additionally, the heterogeneity in M&A treatment captured by interactions of the M&A indicator with our independent variables makes it harder to interpret non-linear models with interaction terms (see e.g., Ai and Norton, 2003). Our main analysis, therefore, employs a simple linear regression framework. However, where possible, we also report robustness checks of non-linear specifications.

3.4 Control groups

To establish innovation effects from M&As, projects exposed to an ownership change deal must be compared to a no-deal counterfactual (control group). In an ideal setting, we would have an experiment with firms acquiring projects randomly, i.e., where the treatment is exogenous. With observational data, such an approach is typically not feasible. We are also not aware of a suitable quasi-experiment that would exogenously shift the transaction propensity.[24]

results, therefore, do not include IPC fixed effects. See further below for an additional analysis of IPCs

[24]For example, a reform that has been extensively used as a source of a quasi-random variation in the US pharmaceutical industry is the installment of Medicare Part D that went into effect in 2006, where drug benefits are provided by private insurance plans that receive premiums from both enrollees and the government. However, it is unclear how Medicare Part D affects the propensity to acquire. Moreover, it only provides a one-off change, whereas our M&A events occur over the time span of 20 years.

We, therefore, use control groups. In our main setting, we use all never-treated projects as our control group and employ a broad range of fixed effects to capture time non-varying characteristics of projects, as explained above.

In addition, we use the patent keywords of Arts et al. (2021) to identify for each treated project the technologically closest, never-treated counterpart within the same development phase, which gives us a set of 342 treated and 342 matched control observations.[25] We use this matched sample in two robustness exercises. First, we restrict our sample to the 342 treated observations and their 342 matched control observations, leaving a pooled sample of 684 observations to run our econometric specifications (including the set of fixed effects). Next, we force each treated project to be only compared to its direct match, by including a set of 342 treated-control pair dummies.

4 Results

4.1 Descriptive evidence

In our sample acquisitions occur overwhelmingly in the early phases of clinical trials. Only a very small minority (3%) of the projects are acquired in the latest phase of clinical trials, i.e. Phase III. Moreover, most of the targets' projects are being taken over by acquirers that are not present yet in antidiabetics: 90 projects by R&D non-incumbents versus 67 projects by R&D incumbents, suggesting as important motive for acquisitions, entry into the diabetes market (see Table D2 in the Appendix).[26]

Table 1 shows some first descriptive statistics on innovation outcomes of acquired projects in early stages. Overall, the termination rate is significantly higher for acquired projects than their controls. They also are less likely to continue and to have a lower likelihood to have new patents post-acquisition, where these differences are more pronounced in early stages.

TABLE 1 HERE

[25] This strategy is in line with other papers on M&As. For example, Gugler et al.(2003) use forced-matching at the firm level, where the matched non-treated firms belong to the same industry as that of the merging firms. In cases with more observables, propensity score matching is frequently employed. Szuecs (2014) match each treated firm to a control firm based on accounting data. Ornaghi (2009a) uses propensity scores on patent expiration and R&D performance. Stiebale and Szuecs (2022) and Bena and Li (2014) use propensity scores in combination with forced matching.

[26] See also Malek et al. (2024) on when acquisitions occur in diabetes, and who takes over whom.

The descriptives in Table 1 show that late-stage cases display different innovation effects, both when compared to the overall sample and to the observations in earlier stages. Differently from early-stage treated projects, treated phase III target projects are not significantly different from their controls on termination and new patents, and they are significantly more likely than their controls to progress to the next stage, i.e., into market launch. Table F1 in Appendix F lists all acquired phase III projects. They largely relate to the effort of relatively large, deep-pocketed pharmaceutical firms without pre-existing launched antidiabetic drugs (see our accompanying paper Malek et al., 2024, for a typology of these acquirers). These companies likely enter the antidiabetic product market by acquiring targets in the late stages of the R&D process. We focus, therefore, our main analysis on the sample of earlier development stages (i.e., preclinical, phase I, and phase II), dropping these phase III projects and their corresponding counterfactuals.[27]

When looking at termination along the various technology and product market dimensions, Table 2 further shows for early stage M&As that the negative effects on target projects are most likely to occur when acquirers are R&D non-incumbents. This contrasts with acquisitions done by R&D incumbents. Target projects are significantly less likely to be terminated when acquirer and target projects are technologically close and share the same future product market (through their MoAs). The descriptive evidence is highly suggestive of the heterogeneity in innovation effects along technology and product market dimensions of the involved parties.

TABLE 2 HERE

4.2 Econometric results

This subsection presents the econometric results of the paper, i.e., the estimation results of equation (1), using the antidiabetics projects in our sample (excluding those treated in phase III in the main analysis). We first present the results, followed by focusing on the heterogeneities that lie behind the main effects. We then present robustness checks. While all the regression equations underlying the graphs are provided in Appendix D, for expositional ease, we present the estimated effects graphically in the text. The three panels of each figure present the effects on the different project-level outcomes, i.e., the

[27]However, our results remain robust when also including these Phase III projects. These regression results can be found in Table D11 in Appendix D.

termination rate, the progression rate to the next phase, and the likelihood of receiving new patents post-transaction. The bars in the figure represent the mean effect with 90% confidence intervals as regards the impact on the acquirers' antidiabetics projects (blue), targets' projects (red), and all projects (green). The projects in the control group (all never-treated projects) are represented by the dashed red line at zero.

Average innovation effects of M&As. Overall, we see in Figure 1, in line with the descriptive results, that M&As have a negative impact on target projects' innovation outcomes, as they have a significantly higher termination rate (left upper panel), a significantly lower progression rate (right upper panel), and a significantly lower probability to generate new patents post-acquisition (left lower panel), as compared to the controls. Also, projects of the acquirer are less likely to create new patents post-acquisition. Furthermore, all projects combined perform worse on all three innovation outcomes.[28]

FIGURE 1 HERE

R&D incumbency and product market incumbency. Figure 2 presents the results when considering the acquiring firm's R&D and product market incumbency. The two most left bars of each panel show the innovation results for acquirers being R&D non-incumbents. Given that their pre-existing antidiabetics portfolio is empty by definition, we can only study the effect of such transactions on the targets' projects (and all projects are, thus, also equal to the targets' projects). Figure 2 shows that projects acquired by R&D non-incumbents suffer significant adverse effects. Target projects are more likely to be terminated, less likely to progress and less likely to produce follow-up patenting.

On the other hand, acquisitions by R&D incumbents (but not product market incumbents) show somewhat smaller negative effects on target projects and have a higher variance, leaving more scope for possible positive cases in this subgroup. These acquisitions, furthermore, show effects on acquirers' projects that are not different from zero. The impact on all projects, however, is still negative.

Figure 2 further shows the effects on projects when the acquirers are not only R&D incumbents but also product market incumbents (right middle three bars of each panel).[29] In this case, the targets' projects do better than when R&D non-incumbents are the

[28] Table D1 reports the regression results. Note further that our results are also robust when using a logit model, as reported in Table D2 in Appendix D. The magnitudes of marginal effects are similar across models.

[29] Table D3 reports these regressions results.

acquirer, most pronounced in lower termination rates, but also in higher progression rates and to some extent in a better follow-up patenting performance. Thus, acquirers that are also product market incumbents makes innovation results of M&As slightly better overall.

FIGURE 2 HERE

Technology twins and MoA overlap. We next look at the role of closeness between targets' and acquirers' projects in both technology and (future) product markets for the effects on innovation of an acquired project. For ease of comparison, Figure 3 shows (i) first again the results for R&D non-incumbents (the three bars at the left in each panel), (ii) the results for R&D incumbents when their projects are only siblings in the technology space and have no MoA overlap (middle three bars in each panel), and (iii) R&D incumbents when their projects are both twins in the technology space and have MoA overlap (right three bars in each panel).[30]

Figure 3 shows that only when targets' and acquirer's projects are twins and when projects share the same MoA, then innovation outcomes of targets' projects are clearly better than for R&D non-incumbents acquisitions. They also do better than for M&As with R&D incumbents possessing more distant projects (projects being siblings and having no MoA overlap), but their variance is higher. The corresponding projects of acquirers in such deals are on average doing better too, but also here their variance is higher. For all projects combined, they do better in terms of termination and progress, but especially in follow-up patenting. Overall, projects do better when being close in technology and product markets, especially when compared to acquisitions by R&D non-incumbents.

FIGURE 3 HERE

Interactions with product market incumbency. Figure 4 presents the results when closeness in technology and (future) product market are interacted with the product market incumbency status of the acquiring firm.[31] Figure 4 shows that when having close projects in both technology and product markets, the acquirer being also a product market incumbent makes a significant difference (three right-most bars). First, projects are significantly less likely to be terminated as compared to the control group, and this for targets, acquirers and all projects combined. All else equal, this is not the case when

[30] Table D4 reports these regressions results.

[31] Table D5 reports the regressions results.

the acquirer is not a product market incumbent. Second, targets projects are significantly more likely to progress, compared to when the acquirer is not a product market incumbent. And third, all projects of targets and acquirers are more likely to produce follow-up patents with product market incumbents being the acquirer, whereas it is the inverse when the acquirer is not a product market incumbent, all else equal.

The results from Figure 4 show that product market incumbency matters for innovation in a good way, but only when acquirers and targets are close in technology and (future) product markets. Interestingly, these effects are not driven by "leader" firms that have the highest market share (and that are less likely to engage in M&As in the first place, see Malek et. al (2024)). Indeed, dropping leading firm acquirers from our analysis does not change our results. This suggests that market share may not be the leading indicator driving the innvation results behind acquiring projects by market incumbents.

FIGURE 4 HERE

At this stage, it is good to remember that the negative results found in Cunningham et al. (2021), namely that product market incumbents are more likely to discontinue target projects when their already launched products projects overlap in the MoA space with the target's projects in development. Cunningham et al. (2021), however, focus on the overlap with the acquirer's launched projects.[32] Our results, instead, provide support for synergies between target and acquirer. Finding such positive innovation effects after acquisitions by product market incumbents require not only that the projects overlap in the MoA space, even if not launched yet, and additionally are close in the technology space.

4.3 Extensions and robustness checks

Matching with technology similar counterfactuals. As a first check, we restrict our sample to the same 342 treated projects, now matched with their technologically closest, never-treated counterparts within the same development phase. This matching results in a sample of 684 observations. Our results remain qualitatively the same, but are more

[32] Appendix E provides a comparison between the projects of our paper and Cunningham et al. (2021). As one can see from Table E1, there are only two target projects in our database that are directly comparable, i.e., where launched products of the incumbent have an MoA overlap with the acquired projects.

significant for the close projects (both in technology and product markets) where the acquirers are product market incumbents (see Figure G1 in Appendix G).[33] In particular, the three categories of projects (targets, acquirers and total) now have a higher possibility to enjoy follow-up patents, compared to the control group.

We then enforce an exact matching, i.e., in addition to our standard fixed effects set, we include a set of 342 treated-control pair dummies, and thus directly compare each treated project with its closest match. Figure G2 shows these results.[34] Due to the small number of observations, their significance is lower, but the general tendency is still there: innovation results are worst for R&D non-incumbents and gradually improve, where the best results are to be found for the cases where R&D incumbent acquirers are also product market incumbents and at the same time target and acquirers' projects are close in technology and product markets.

Clustering of errors. Our base assumption is that errors are *i.i.d.*, but the error term might not be independent across observations. The first plausible source of correlation relates to the firms' portfolio. Projects belonging to the same firm might experience common shocks, since decisions are often made at a firm level. Figure G3 presents a regression analysis where standard errors are clustered at the firm level.[35] The main results do not change for the progression and termination outcome variables. As regards to patenting, the confidence intervals are slightly widened. Although this renders the overall patenting impact neutral rather than positive, this results still imply that the combination of incumbency and closeness in product and technology markets generates better outcomes than all other transactions.

The second plausible source of correlation relates to the projects involved in the same transaction. The analysis presented in Figure G4 employs the sample with matched counterfactuals (684 observations) such that both the treated and the control projects can be assigned to a specific transaction, with the standard errors clustered at the transaction level.[36] Compared to the model reported above on "matching with technology similar counterfactuals," the results remain fully robust.

Outcomes conditional on progress. We further perform a robustness check to see how the progression and patenting outcomes change when only considering non-terminated

[33]Table D6 presents the regression results.
[34]Table D7 reports the regressions results.
[35]Table D8 reports the regressions results.
[36]Table D9 reports the regressions results.

projects, as terminated projects by definition cannot progress nor produce follow-up patents. Figure G5 shows that the main results on progress and new patents still hold: innovation results are worst for R&D non-incumbents and gradually improve with the best results for the cases where R&D incumbent acquirers are also product market incumbents and at the same time target and acquirers' projects are close in the product and technology space.[37] Conditional on not being terminated, especially the target projects are more likely to continue, and more likely to receive new patents.

Including Phase III projects. As can be seen in Figure G6, when including the few Phase III projects in the analysis, the noisiness of the results increases, which is in line with the different innovation patterns of the Phase III projects we detailed above.[38] However, the main results and tendencies remain.

Different cutoffs to define technologically close projects (twins). Figure G7 shows the estimated effects of M&As when varying the cutoff value for the definition of twin projects (based on our text similarity measure).[39] We use first a looser definition (90th percentile = 0.11), compare it to our default value (95th percentile = 0.16), and also uses a tighter definition (99th percentile = 0.29). As expected, effects are less strong for a looser definition of closeness, whereas a tighter definition does not make much difference, indicating that our baseline value is where it makes a difference.

Alternative measures of closeness. As including the dimension of technological closeness is, we believe, one of the main contributions of this paper, we check our results when using different measures of technological closeness. The standard measures used in the technology literature are much more aggregate and/or indirect, using technology class information or overlap in citations, than our text-based measure to assess technology closeness between projects. The first column in figure G8 uses our text-based definition of technological closeness, which we believe is the most detailed measure to assess similarity between projects. The second column uses backward patent citations to proxy technological closeness. The third column uses Jaffe's similarity measure based on co-occurrences of IPC patent groups as a measure for technological closeness (Jaffe, 1986). These measures are combined with the MoA overlap and market incumbency status of the acquirer. Our main results remain robust for the various alternative measures of closeness, but are most

[37] Table D10 reports the regressions results.
[38] Table D11 reports the regressions results.
[39] Table D12 reports the regressions results.

clear for our granular measure.[40]

Antidiabetics focus. While we have excluded transactions between conglomerates, Figure G9 and the underlying regressions in Table D14 presents robustness checks when excluding transactions that do not explicitly mention diabetes or insulin (see footnote 16).

We further ran robustness checks, where we include as control variables the total firm-level number of ex-diabetes patents. This control serves as a proxy for a firm's ex-diabetes innovation activity, where one could imagine that if a firm is very active outside diabetes, then a transaction that also involves diabetes projects might lead to different innovation effects on these diabetes projects, as they are not the core of the transaction. We present these results in Figure G10 (where the regression can be found in table D15). Our results show that all our effects go through, further indicating that we indeed identify transactions where diabetes is at the core, and thus, innovation effects of our acquisitions are not influenced by firms' activity in other pharmaceutical markets.

5 Conclusions

This paper examines the impact of M&As on innovation in the antidiabetics market, using a comprehensive dataset that tracks the lifecyle of all individual projects in development between 1997 and 2017. We consider not only the product market position of the acquiring firm, but also the positions of both the acquirer and the target projects in the technology space and future product market.

We find that, on average, acquired projects exhibit weaker innovation outcomes than comparable non-acquired projects. This pattern is particularly pronounced for early-stage acquisitions involving small targets. Importantly, however, these negative outcomes are not necessarily indicative of so-called "killer acquisitions" aimed at preempting competition. Rather, they reflect a more nuanced relationship between acquisition dynamics and innovation trajectories. For example, firms that were not previously active in the antidiabetics market tend to acquire projects that subsequently perform poorly in terms of innovation outcomes. Given their lack of prior presence in both technology and product markets, these negative outcomes are unlikely to be driven by anti-competitive motives.

[40] Tables D16 and D17 report the regressions results.

Although acquired projects generally exhibit less successful innovation outcomes compared to their counterfactuals, we identify a distinct subset of transactions that lead to improved innovative performance. These positive effects arise when three conditions are simultaneously met: (i) the acquirer holds an incumbent position in both the product and technology domains, (ii) the projects of the acquiring and target firms are technologically proximate, and (iii) they share the same mechanism of action (MoA). In such cases, we observe a notable increase in post-acquisition patenting activity, not only for target projects, but also for acquirer projects, consistent with the realization of technological synergies and two-way knowledge spillovers within the new merged entity. These findings indicate that M&As can indeed foster innovation, but only under conditions of strong strategic and technological complementarity between the merging firms.

Our results have implications for merger policy and antitrust enforcement. Traditional frameworks, which emphasize product market concentration and product overlap, may overlook the innovation risks posed by early-stage, technology-focused acquisitions. Our findings suggest that meaningful innovation effects already take place in these early stages, both positive and negative. The size and sign of these effects depend critically on technological proximity and incumbency, dimensions that are not typically captured in standard merger reviews. As such, there is a compelling case for expanding the scope of antitrust assessment to explicitly consider the technological characteristics of merging firms and their projects, particularly in R&D-intensive industries where early development decisions shape long-term innovation trajectories.

Future research could extend this work in several directions. First, incorporating additional measures of involved technologies -such as novelty, complexity, or disruptiveness could offer deeper insights into the types of innovation most affected by M&A activity and their likely effects. Second, analyzing post-acquisition knowledge flows through patent citations, technology reuse, and inventor mobility would help further identifying the synergy mechanisms as potential drivers of positive outcomes. Finally, the framework developed in this study is applicable beyond antidiabetics and can be scaled to other therapeutic areas. This offers a path toward more comprehensive, data-driven evaluations of how M&A activity shapes the innovation landscape in the life sciences and other high-innovation patent-intensive sectors.

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Tables

Tab. 1: Summary statistics - Outcomes of M&A vs. non-M&A for Targets

	Target		
	(1)	(2)	(3)
	No M&A	M&A	p-value
Termination			
Full sample	0.16	0.39	0.00
Late	0.00	0.40	0.14
Early	0.16	0.39	0.00
Progression			
Full sample	0.38	0.22	0.00
Late	0.00	0.60	0.04
Early	0.39	0.20	0.00
Patenting			
Full sample	0.38	0.18	0.00
Late	0.60	0.20	0.24
Early	0.38	0.18	0.00
Observations	314	314	314

This table presents summary statics for the progression, termination, and follow-up patenting outcome variables for target projects depending on the M&A status (columns) and project characteristics (panel rows). Each of the panels presents descriptive evidence for one outcome variable. In each panel, the overall mean (and corresponding p-value for their differences) are presented in the first row. The second and third row use the subsample of late or early treated projects.

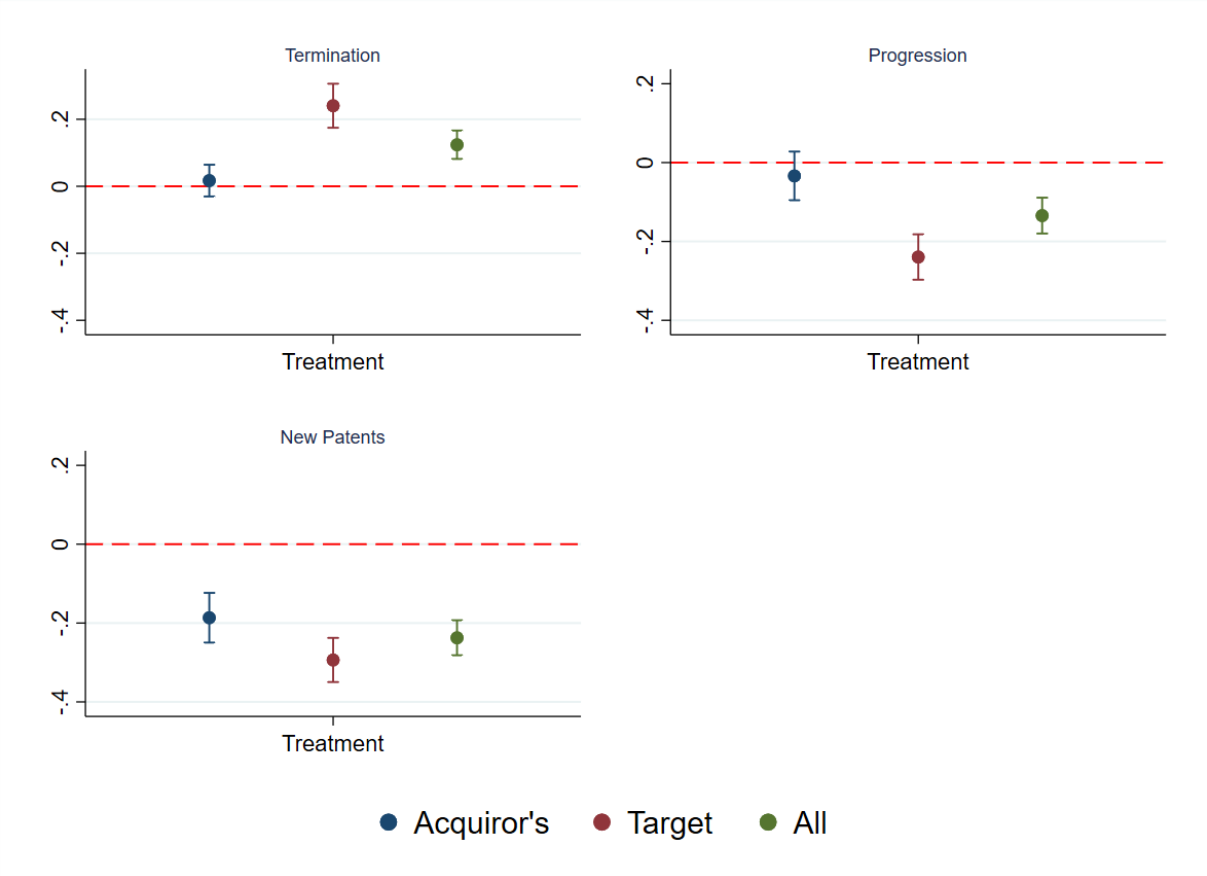
Tab. 2: Summary statistics - Termination in M&As vs. non-M&As

	Acquirer			Target		
	(1)	(2)	(3)	(4)	(5)	(6)
	No M&A	M&A	p-value	No M&A	M&A	p-value
Termination						
Full sample	0.06	0.14	0.01	0.16	0.39	0.00
Early	0.07	0.16	0.01	0.16	0.39	0.00
Early: R&D non-Inc				0.08	0.45	0.00
Early: R&D Inc - no MoA	0.07	0.17	0.01	0.24	0.38	0.13
Early: R&D Inc - Twin + MoA	0.00	0.08	0.33	0.50	0.08	0.02
Early: R&D Inc - non Twin+MoA	0.07	0.16	0.01	0.23	0.38	0.09
Observations	370	370	370	314	314	314

This table presents summary statistics for the termination outcome depending on the M&A status (columns) and project characteristics (panel rows). In each panel, the overall mean (and corresponding p-value of their differences) are presented in the first row. The columns (1)-(3) use the subsample of the acquirer projects, columns (4)-(6) show the target projects.

Figures

Fig. 1: Effects of M&As - Average effects

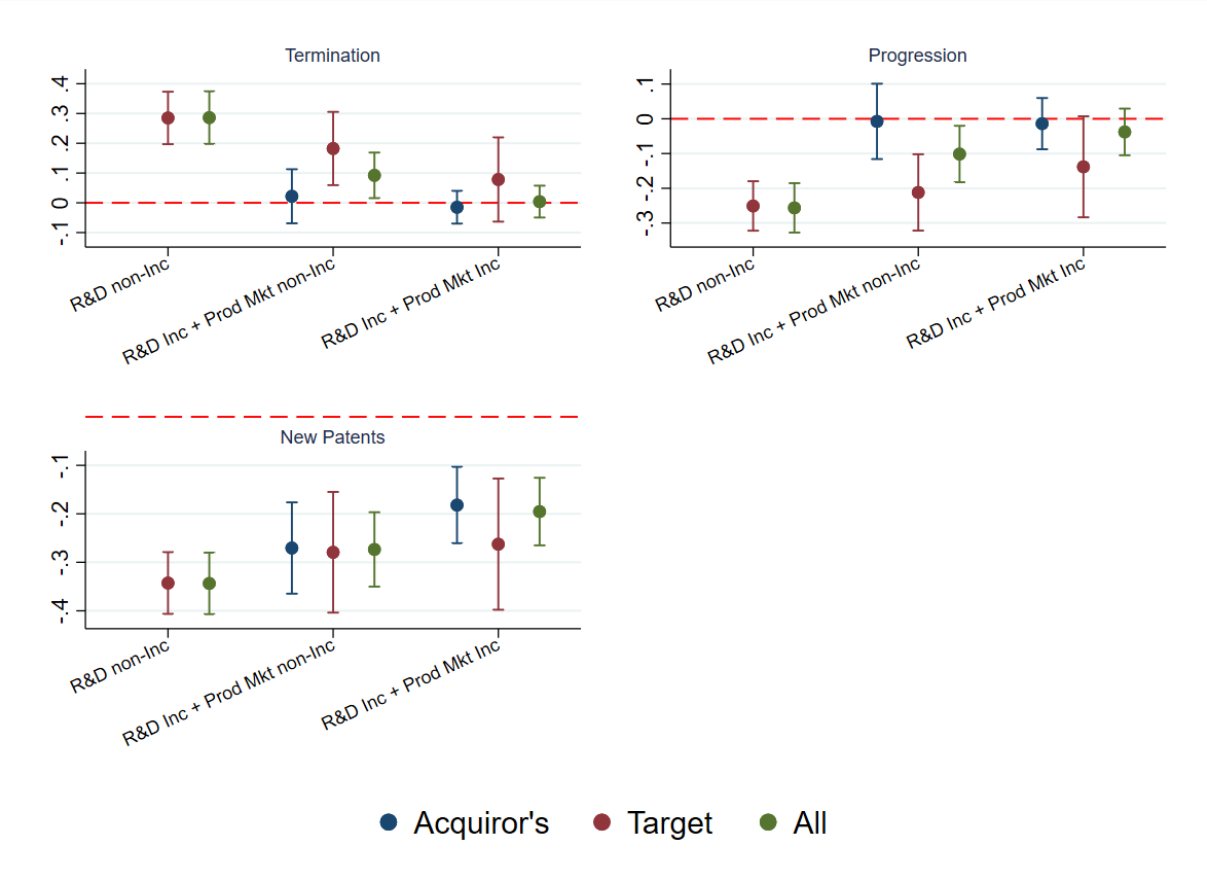


Note: This figure visualizes the estimated effects of M&As compared to all never treated projects (no matching). The underlying regression has the following form:

$$Outcome_{ip} = \beta_{0p} + \beta_{1p} Treated_{ip} + \beta_{2p} FE_{ip} + \epsilon_{ip},$$

where observation i corresponds to a project-phase and p represents the acquirer (A), target (T), or all $(A+T)$ project sets, respectively. We report robust standard errors. The bars give the mean of the total effect with 90% confidence intervals for the treatment group. The effects on acquirer's projects are plotted in blue, on target projects in red, and combined in green. The red dashed line highlights a zero effect. Full regression results are presented in table D3.

Fig. 2: Effects of M&As - R&D incumbency and product market incumbency

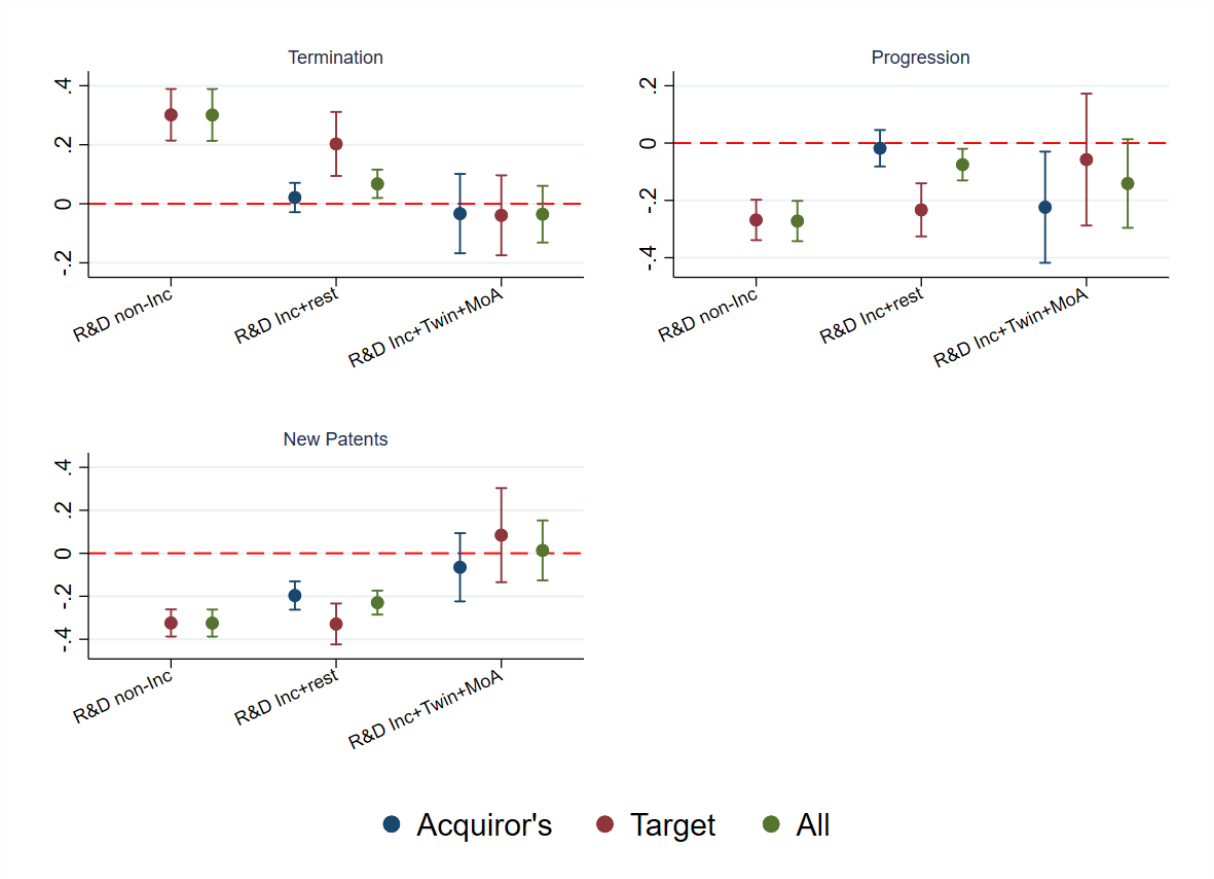


Note: This figure visualizes the estimated effects of M&As depending on both R&D incumbency and market incumbency status, compared to all never treated projects (no matching). The underlying regression has the following form:

$$Outcome_{ip} = \beta_{0p} + \beta_{1p} R\&DNonInc_{ip} + \beta_{2p} R\&DInc_{ip} + \beta_{3p} MktInc_{ip} + \beta_{4p} MktInc_{ip} \times R\&DInc_{ip} + \epsilon_{ip}.$$

Observation i corresponds to a project-phase and p represents the acquirer (A), target (T), or all ($A+T$) project sets, respectively. We report robust standard errors. The bars give the mean of the total effect with 90% confidence intervals for the respective exclusive treatment groups (β_1 for R&D non-incumbents, β_2 for R&D incumbents and market non-incumbents, and $\beta_2 + \beta_3 + \beta_4$ for R&D incumbents and market incumbents). The effects on acquirers' projects are plotted in blue, on target projects in red, and total in green. Note that R&D non-incumbents have an empty antidiabetics portfolio before a transaction and, hence, the acquirers' side cannot be analysed. The red dashed line highlights a zero effect. Full regression results are presented in table D5.

Fig. 3: Effects of M&As - Technological closeness and MoA overlap

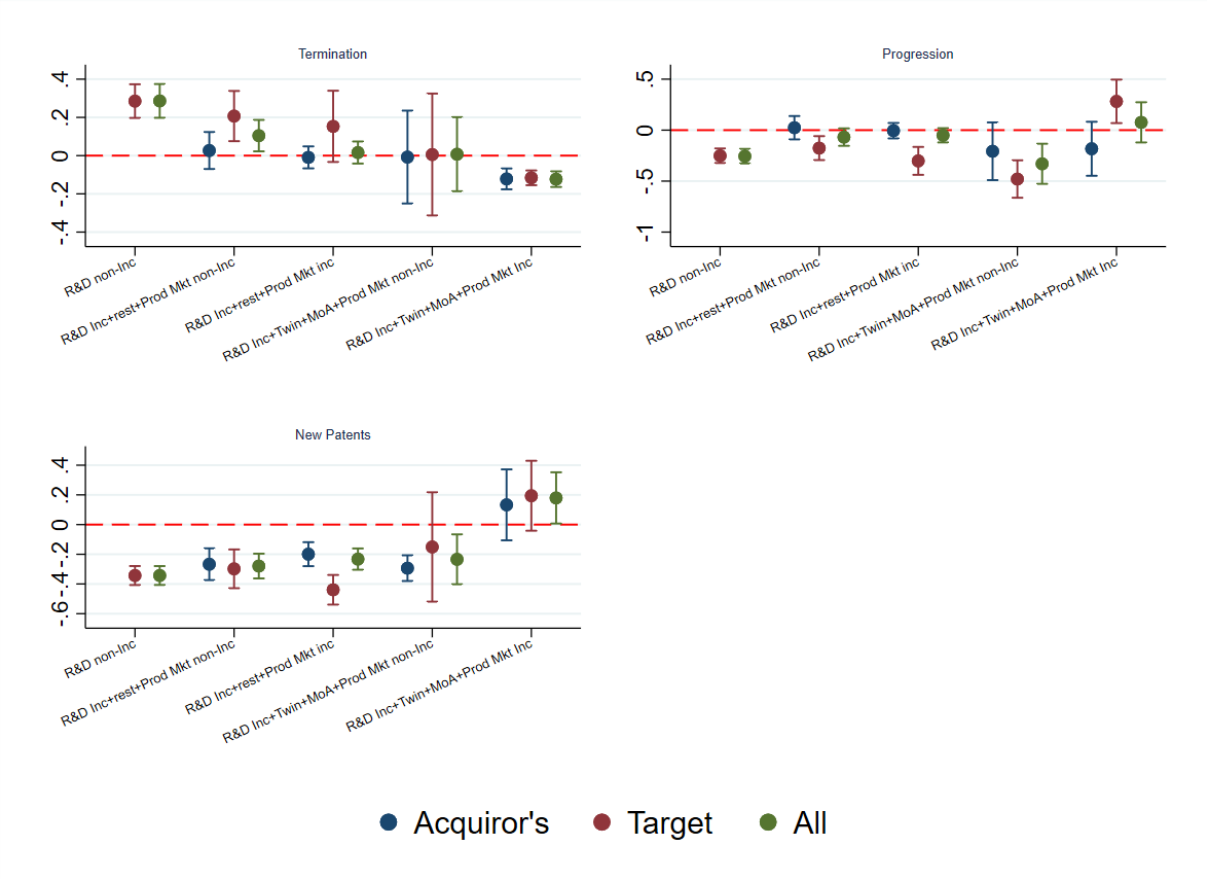


Note: This figure visualizes the estimated effects of M&As depending on the combination of technological closeness and MoA overlap, compared to all never treated projects (no matching). The underlying regression has the following form:

$$Outcome_{ip} = \beta_{0p} + \beta_{1p} R\&DNonInc_{ip} + \beta_{2p} R\&DIncRest_{ip} + \beta_{3p} R\&DIncTwinMoA_{ip} + \epsilon_{ip}.$$

Observation i corresponds to a project-phase and p represents the acquirer (A), target (T), or all ($A+T$) project sets, respectively. We report robust standard errors. The bars give the mean of the total effect with 90% confidence intervals for the respective exclusive treatment groups (β_1 for R&D non-incumbents, β_3 for R&D incumbents with technologically close projects with MoA overlap, and β_2 for all other projects of the R&D incumbents, namely technologically distant projects with or without MoA overlap and technologically close projects without MoA overlap). The effects on acquirer projects are plotted in blue, on target projects in red, and total in green. Note that R&D non-incumbents have empty antidiabetics portfolio before a transaction and, hence, the acquirer's side cannot be analysed. The red dashed line highlights a zero effect. The red dashed line highlights a zero effect. Full regression results are presented in table D6.

Fig. 4: Effects of M&As - Technological closeness, MoA overlap, and product market incumbency



Note: This figure visualizes the estimated effects of M&A depending on the combination of technological closeness, MoA overlap, and market incumbency compared to all never treated projects (no matching). The underlying regression has the following form:

$$\begin{aligned} Outcome_{ip} = \beta_{0p} + \beta_{1p} R\&DNonInc_{ip} + \beta_{2p} MktInc_{ip} + \\ + \beta_{3} R\&DIncRest_{ip} + \beta_{4p} R\&DIncRest_{ip} \times MktInc_{ip} + \\ + \beta_{5p} R\&DIncTwinMoA_{ip} + \beta_{6p} R\&DIncTwinMoA_{ip} \times MktInc_{ip} + \epsilon_{ip}. \end{aligned}$$

Observation i corresponds to a project-phase and p represents the acquirer (A), target (T), or all ($A+T$) project sets, respectively. We report robust standard errors. The bars give the mean of the total effect with 90% confidence intervals for the respective exclusive treatment groups (β_1 for R&D non-inc, $\beta_2+\beta_5+\beta_6$ for R&D inc and market inc with technologically close projects with MoA overlap, β_5 for R&D inc and market non-inc with technologically close projects with MoA overlap, β_3 for all other projects of the R&D inc and market non-inc, and $\beta_2+\beta_3+\beta_4$ for all other projects of the R&D inc and market inc). The effects on acquirer projects are plotted in blue, on target projects in red, and all in green. R&D non-incumbents have empty antidiabetic portfolios before a transaction and hence, the acquirer's side cannot be analysed. The red dashed line highlights a zero effect. Full regression results are presented in table D7.

Appendix A: Patent matching

This appendix is our manual to matching patents to antidiabetic projects. According to our knowledge, there is no publicly available database providing project-patent links beyond launched drugs (through the Orange Book).[41]

Patent databases

We focus on US patents. Three sources of patent data are used: the USPTO patent database[42], the PATSTAT database, and the LENS patent database.[43] In these databases, we use the information regarding patent application dates, patent grant dates, patent extensions, priority dates, IPC patent classes, patent families, patent assignees, and backward patent references.

Our matching starts by establishing so-called 'candidate patent sets' for each of the 2387 projects in the sample. The candidate patent set contains all granted US patents of the firms that were involved in the development of a project (the originator, the final owner, and all owners in the chain in between) and that were filed for between the initiation date and the discontinuation date of a project (retrieved from the progression through clinical trials).[44] To narrow down the patent universe to technologies which plausibly relate to pharmaceutical markets and drug development, we follow Smoch (2008) and own analysis based on the FDA's Orange book and consider only patents with at least one IPC subclass in A61K, A61M, A61P, C07C, C07D, C07F, C07K, C07H, C08F, C08G, C12N or C12P. After this step, each project has a set of patents filed for during its lifetime and belonging to the relevant firms - the so-called candidate set - in which we look for the patents relevant for a specific project.

[41] Known private databases (e.g., Cortellis) do not provide sufficient coverage and are nontransparent as to how they assign patents to projects.

[42] Available at https://patentsview.org/download/data-download-tables

[43] Available at https://lens.org

[44] To identify the patents belonging to each candidate set, we perform fuzzy string matching on the company names and patent assignee names. To improve precision of the matching routine, we first standardize the names. We remove the legal forms of companies, clean the names from non-alphanumerical characters, remove generic words and combinations of words that only distinguish separate legal entities, but refer to the same underlying company (e.g., "pharmaceutical products", "intellectual properties", "healthcare systems"). Thereafter, we standardize the company names by taking the first word of the company's name, keeping the most frequent and using it to substitute the other names referring to that company. Following the fuzzy string-matching routine, we manually checked the correctness on a random sub-sample of firms. The procedure yielded a minimum of false matches.

There are two major issues when searching for patents belonging to a specific project. First, there is significant heterogeneity between the projects in our sample, ranging from small molecule drugs to large molecule drugs. Second, a substantial number of projects in the Pharmaprojects database misses information along the relevant dimensions. Our matching procedure therefore consists of several complementary approaches that try to overcome these issues.

Chemistry matching

Patents for "small molecule" or chemical drugs are matched based on their chemical properties. Using the Surechem[45] database and various identifiers (CAS numbers, SMILES Chemical structures, and UNII identifiers), we link a project's underlying chemical compounds to PubChem[46]. PubChem contains information on the patents protecting specific molecules for some chemical entities. If we find an overlap between the "candidate set" and the set of patents retrieved from PubChem, we consider these patents as assigned to a project[47]. This procedure results in 411 matches (these are then excluded from further matching).

Gene matching

Patents for "large molecule" or biological drugs are matched based on gene sequences. Since the early 1990s, US patent applications claiming genes as intellectual property must disclose the exact DNA or protein sequences claimed in the text of the patent. The sequences are listed in the USPTO patent applications in a standard format, labeled with the text "SEQ ID NO." Bio-informatics methods can be used to compare these sequences against the census of human genome to annotate each sequence with standard gene identifiers. In turn, these can be linked to outside databases, including the Pharmaprojects database.

[45]SureChEMBL provides free access to chemical data extracted from the patent literature. Available here: ftp://ftp.ebi.ac.uk/pub/databases/chembl/SureChEMBL/

[46]PubChem is a publicly available, open chemistry database at the National Institutes of Health (NIH). Available here: https://pubchemdocs.ncbi.nlm.nih.gov/downloads

[47]If a match on the company level is found but the patent lies outside of the development window of a project, we check whether other members of the patent's family in the development window of a project. If so, this is considered a match as well.

We broadly follow the methodology suggested in Sampat and Williams (2019). First, we extract standard gene identifiers (known under Entrez gene ID) from the Pharmaprojects database. Using the GeneBank generated crosswalks[48], we connected each of the gene IDs to a list of mRNA, RNA and protein RefSeq accession/version numbers and extracted the corresponding nucleotide sequences from the GeneBank's webpage, including start and end positions of the chain in the sequence, if applicable. To capture the full universe of known sequences relating to a particular gene ID, we utilize both the sequences relating to the annotated human genome as well as the sequences maintained independently of the annotated genome.

Following the methodology pioneered by Jensen and Murray (2005), we use the BLAST (Basic Local Alignment Search Tool) search engine to compare the above sequences to the census of sequences disclosed in the US patents. To arrive at the true set of matches, we only consider blast matches with an E-value of less than 1e-50[49]. This yields a final mapping between projects and patents referring to the respective gene via the disclosed sequences. We only consider patents as assigned to a project when they fall within the development window and belong to one of the relevant firms. This procedure results in 222 matches (these are then excluded from further matching).

MoA keyword matching

We complement the two above approaches with a text analysis using the mechanism of action (MoA). For projects with a known MoA, we first perform a cleaning procedure to standardize MoA names, obtaining a set of tokens ("keywords").[50] Using a combination of TF-IDF algorithms and manual checks, we also retrieve all relevant synonyms relating to a particular MoAand add those to the relevant keywords.[51] To find the counterparts of these keywords in patents and establish matches, we utilize the database of Arts et al (2021). Arts et al (2021) pre-process the text in the patents by concatenating the title and abstract and claims text, lower-casing the text, tokenizing all words, and eliminating

[48]Available here: ftp://ftp.ncbi.nih.gov/refseq/release/release-catalog/release97.accession2geneid.gz

[49]Sampat and Williams (2019) use an E-value of exactly 0. However, we apply a less strict threshold as our threshold level is commonly applied in the field and a threshold of strict zero might be too restrictive.

[50]This includes tokenization, removal of special characters or words comprised of a single letter only, and stemming using Porter's stemmer.

[51]For example, the MoA "glucagon-like peptide" is often only mentioned using its abbreviation glp1 or glp-1. Or, the fibroblast growth factor 21 is known under fgf21 or fgf-21. As well, the DPP-IV mentioned above is sometimes referred to as DPP-4, DPP4 or dipeptidyl peptidase 4 inhibitor.

stop words based on a manually compiled list, removing words with only one character, numbers, and words that appear only once across all patents. We pair a patent to a project if all MoA keywords or an abbreviation are found in a patent document. We then check that only patents are kept that belong to the relevant firms and which were applied for during the development window of a drug project. This procedure results in 487 matches (these are then excluded from further matching).

Remaining matching

If no match for a project has been found with the above methods, we proceed by using various plausible exclusion restrictions. For example, projects with a single patent in the candidate set are considered matched. Similarly, all patents are assigned to a project if the firm has only one project under development. We also assigned projects to zero patents if a firm had no US granted patent (we checked all these instances manually to verify the absence of the US patents). Lastly, the 93 launched projects were matched to patents based on information in the FDA's Orange Book. In total, this yielded an additional 660 matches (these are then excluded from further matching).

The remaining set of 570 unmatched projects were checked manually. For each of these projects, the patent text was compared to the above project's properties (where available). We hired a chemistry student to then read these text fields, compare those, and decide which patents from the set of candidate patents should be relevant for a particular project. This resulted in another 161 matched projects (these are then excluded from further matching). This leaves us with a final sample of 1941 matched projects and 437 unmatched projects, representing a matching rate of 81%. A total of 4999 patents were assigned to the projects. We drop the matched projects from our sample.

Summary statistics on matching

Although the Orange Book only considers drugs that are launched on the market, and thus only captures a selected subset of successful projects not representative of the entire pipeline, it is currently the only source of information on patent-project links. Below, we present basic descriptive statistics to put the results of our matching procedure into perspective.

Tab. A1: Comparison of patent statistics between the Orange Book projects and our matched project sample

Matched sample			
Patents		Projects	
Mean - projects per patent	1.8	Mean - patents per project	4.32
Max - projects per patent	25	Max - patents per project	113
Share of patents with single assigned project	67.3	Share of projects with single assigned patent	38.14
		Share of projects with no assigned patent	9.64
Orange Book			
Patents		Projects	
Mean - projects per patent	1.95	Mean - patents per project	10.91
Max - projects per patent	12	Max - patents per project	46
Share of patents with single assigned project	66.16	Share of projects with single assigned patent	9.76
		Share of projects with no assigned patent	0

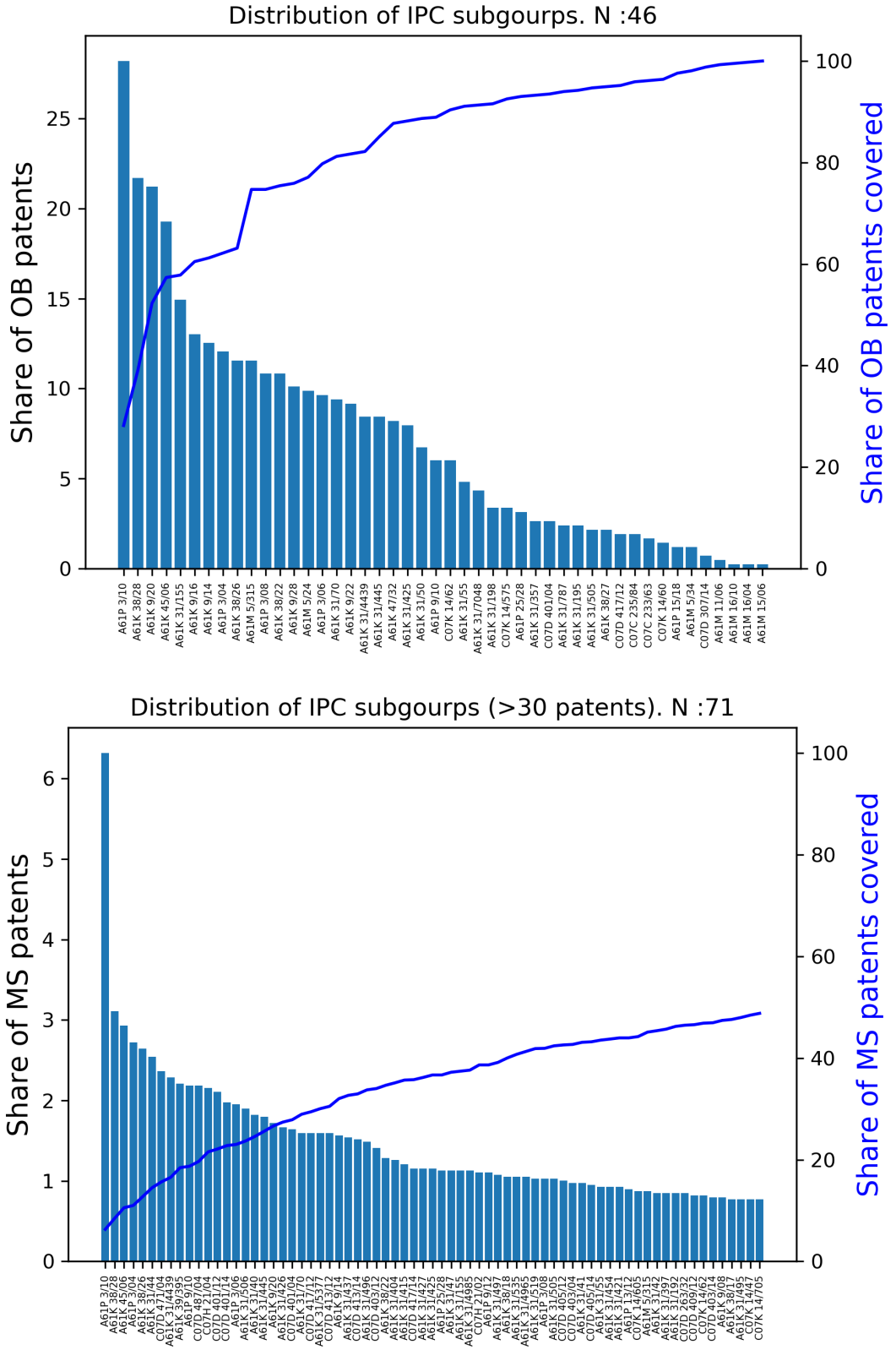
Since a project can have more than one patent assigned, we present a project-centered and a patent-centered perspective in Table A1. Overall, the numbers lend credibility to the outcome of the patent matching. From the patent perspective, the average number of projects assigned per patent amounts to two across both samples and in both cases around 67% of patents assigned to a single project. From the project-level perspective, a project has on average 4.32 patents in our matched sample and almost 11 patents in the Orange book. Considering that our matched sample includes a set of projects in early development phases, a higher fraction of the projects have only a single patent assigned compared to the Orange Book (38% in the matches sample vs. 10% in the Orange Book). In line with the findings of Argente et al (2019), the average number of patents per project in the matched sample is lower than in the Orange Book sample.

Figure A1 provides further a comparison between the types of patents that were assigned to the projects (lower part) and how these compare to the Orange book (upper part). Using the IPC classification subgroups level (the most granular classification available in the IPC classification), we plot the distributions of the occurrence of the IPC classes in the two sets. We should expect that whilst the matched sample will include more IPC categories compared to the Orange Book due to the dispersion of early-stage R&D activities, the top classes in both sets should be similar.

The distribution of the matched sample is broader compared to the Orange Book, and each IPC sub-group occurs less frequently. For example, the most frequent subgroup A61P 3/10 occurs in more than 25% of patents in the Orange Book and in slightly more

than 6% of cases in our matched sample. However, comparing the ordering of the different IPC subgroups, we find that among the most five frequent groups in each sample, three subgroups are shared and have high relevance to antidiabetics drugs: A61P 3/10 - drugs for hyperglycaemia, e.g. antidiabetics, A61K 38/28 - insulins, and A61K 38/28 - Mixtures of active ingredients without chemical characterization, e.g. antiphlogistics and cardiaca. In addition, the third most frequent subgroups in the matched sample - A61K 38/26 - refers to Glucagons. This shows that the matched patents relate closely to diabetes and at least the most frequent technological subgroups closely mirror the sample of drugs launched on the market.

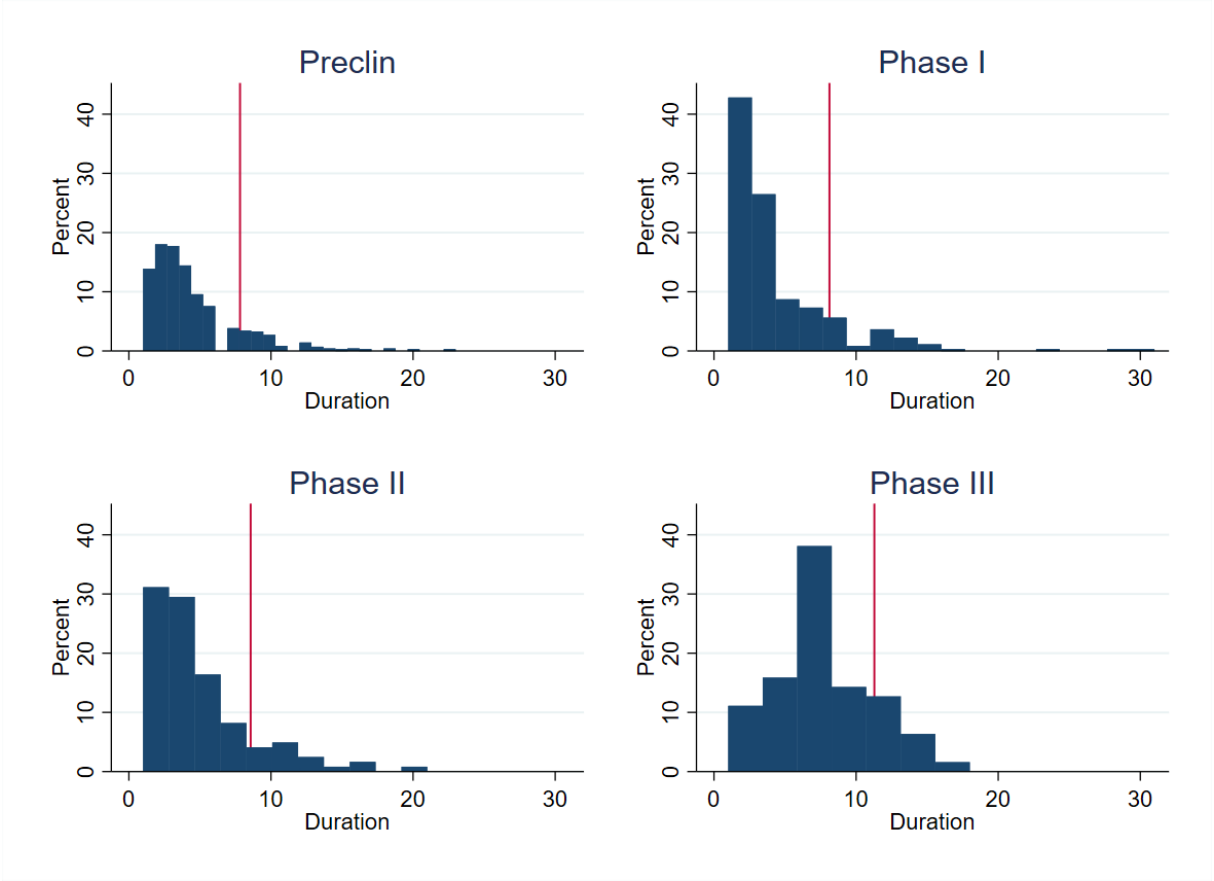
Fig. A1: Distribution of IPC subgroups in Orange Book and matched samples



Appendix B: Distribution of phase durations

Figure B1 shows the distribution of project durations for the different phases of the pharmaceutical R&D process. The blue bars represent the distribution of projects, the red line then plots the critical value of mean plus one standard deviation which is used in our analysis as the cutoff to define terminations.

Fig. B1: Distribution of phase durations and Termination cutoff



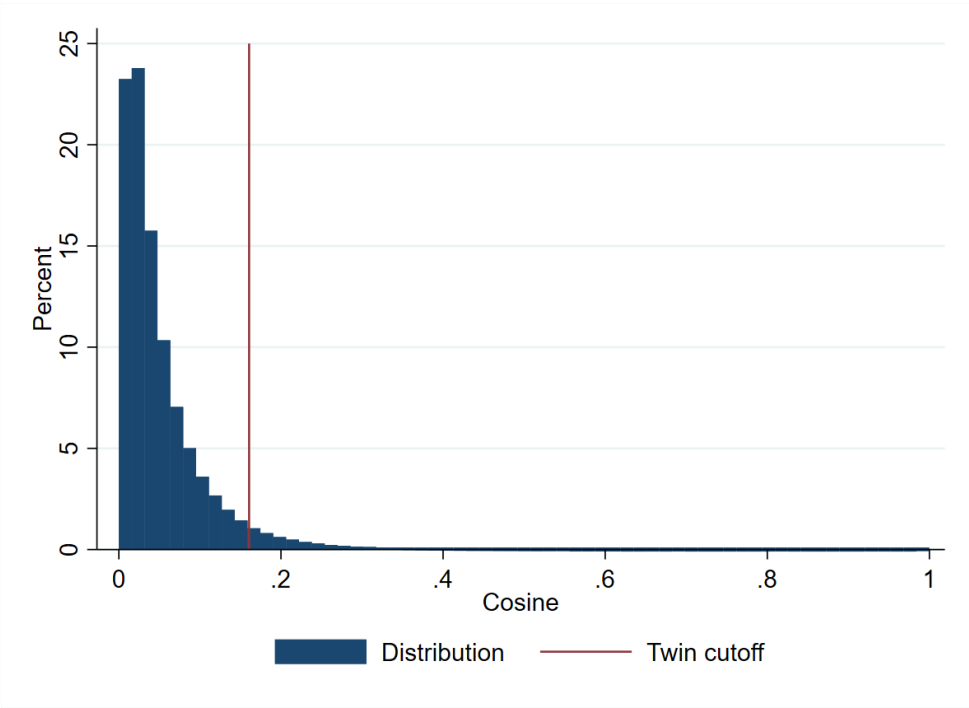
Appendix C: Construction of the technology variables

This section explains how we define the measures of technological closeness between individual projects, and how we split the treated projects between *Twins* and *Siblings* to assess the role of technological closeness in M&As.

We measure the technology closeness by computing cosine similarity between the text of patents we assigned to the acquirer's and target projects (for details on this procedure, please see Appendix B in Malek *et al* (2021). As a starting point, we match each US patent attached to our projects to the database of Arts *et. al* (2021) who provide patent text in from of standardized and pre-cleaned keywords stemming from patents titles, abstracts, and claims. For each project, we pool keywords together. This then constitutes a vector, characterizing each project by a set of keywords.

We use these vectors to compute cosine similarity between any pair of projects in our sample according to formula $Cosine(A, B) = \frac{A \cdot B}{\|A\| \cdot \|B\|}$, yielding more than 2.4 million observations with the following distribution.

Fig. C1: Distribution of technological similarity



To determine whether a particular project was technologically close (in which case it is called a *Twin*) or technologically distant (in which case it is called a *Sibling*) we use the cut-off value equal to 95th percentile (or 0.16) of the above distribution.

Fig. C2: Examples: construction of the closeness variables

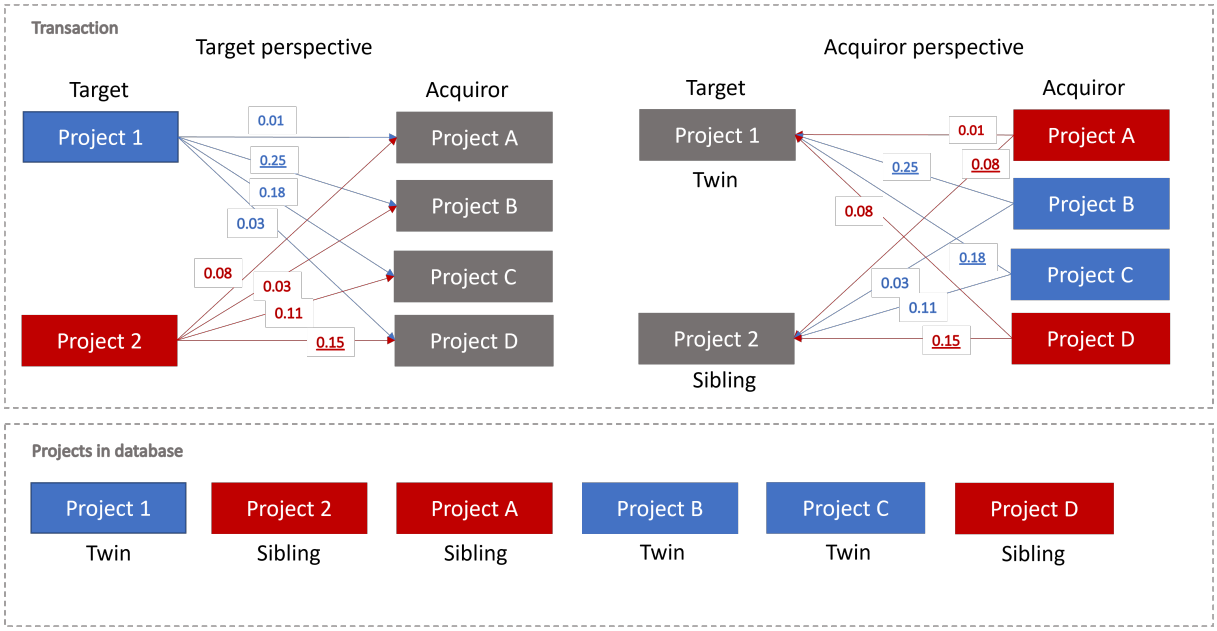


Figure C2 illustrates how these closeness variables are constructed in practice on an example of a transaction. The transaction involves altogether six treated projects. An acquirer owns a portfolio of four projects - A,B,C,D - and is acquiring a target with two projects - project 1 and 2. The left part of the figure presents the target perspective and shows how target project 1 and project 2 technologically relate to the projects of the acquirer. Project 1 is the most similar to acquirer's project B - with a cosine value of 0.25. This project exceeds our cutoff and would be thus categorized as technologically close - a *Twin*. Project 2 is the most similar to project D - with a cosine value of 0.15. This project does not exceed our cutoff and would be thus categorized as technologically distant - a *Sibling*. Analogically, from the acquirer's perspective, projects A and D are the most similar to project 2 (0.08 and 0.15, respectively) and would be both categorized as *Siblings*, while projects B and C are the most similar to project 1 (0.25 and 0.18, respectively) and would be both categorized as *Twins*. To summarize, the transaction involves 6 treated projects - 1 target twin, 1 target sibling, 2 acquirer twins and 2 acquirer siblings.

Appendix D: Tables and estimations

Tab. D1: Variable definitions

Termination	Equals one if the project has not proceeded to the next development phase and at the same time stayed in the same phase exceptionally long (beyond the mean + one standard deviation of the phase duration distribution).
Progression	Equals one if the project has proceeded to the next development phase.
New Patents	For the treated projects, the variable equals one if at least one new patent was filed after the project has experienced an M&A transaction. For the matched (never-treated) projects (the counterfactual group), the variable equals one if at least one new patent was filed following after the M&A transaction of the matched treated project.
Early	Equals one if the project is in the preclinical stage, Phase I, or Phase II of clinical development.
Late	Equals one if the project is in Phase III of clinical development.
Acquirer	Equals one if the project belongs to a firm that is acquiring projects.
Target	Equals one if the project belongs to a firm that is selling projects.
Market Incumbent	Equals one if the project belongs to company with marketed antidiabetic drugs.
R&D Incumbent	Equals one if the acquirer has an active antidiabetic R&D portfolio before an M&A transaction.
R&D non-Incumbent	Equals one if the acquirer has no active antidiabetic R&D portfolio before an M&A transaction.
Twin	Equals one if the project of the acquirer (target) is technologically close to the project of the target (acquirer) in an M&A transaction. The default threshold for being technologically close is equal to the 95th percentile of the cosine similarity distribution between all projects (value 0.16).
Sibling	Equals one if the project of an acquirer (target) is not technologically close to the project of the target (acquirer) in an M&A transaction.
MoA	Equals one for the project of an acquirer (target) if there is at least one other project of the target (acquirer) in an M&A transaction with the same mechanism of action (MoA).
no MoA	Equals one for the project of an acquirer (target) if there was no other project of the target (acquirer) in an M&A transaction with the same MoA.

Tab. D2: Number of M&As: treatment variable splits

	Acquirer projects	Target projects	All projects
Phase:			
Early phase	167	152	319
Late phase	18	5	23
Acquirer R&D incumbency:			
R&D Non-Incumbent	0	90	90
R&D Incumbent	185	67	252
Splits conditional on R&D incumbency:			
R&D Inc + Prod Mkt non-Inc	52	40	92
R&D Inc + Prod Mkt Inc	133	27	160
Technology closeness:			
Sibling	122	39	161
Twin	63	28	91
MoA overlap:			
No MoA overlap	168	51	219
MoA overlap	17	16	33
Tech + MoA:			
Sibling + no MoA overlap	118	36	154
Sibling + MoA overlap	4	3	7
Twin + no MoA overlap	50	15	65
Twin + MoA overlap	13	13	26
Observations	185	157	342

Note: R&D incumbency of the acquirer determines the existence of its antidiabetics portfolio before acquiring a project (the portfolio of R&D non-incumbents is empty). Furthermore, in our database, all firms with launched products work on R&D projects. Thus, the category of R&D non-incumbent + market incumbent does not exist.

Tab. D3: Average effects

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
Treated	0.124***	-0.134***	-0.237***
	(0.026)	(0.028)	(0.027)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.078	0.125	0.240

Panel B: Acquirers and targets

	Acquiror's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
Treated	0.017	-0.034	-0.187***	0.240***	-0.239***	-0.294***
	(0.029)	(0.038)	(0.038)	(0.040)	(0.035)	(0.034)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	1838
Adj. R2	0.053	0.122	0.245	0.098	0.128	0.266

Notes: This table shows the results of the OLS regressions measuring the effect of M&As on all projects (panel A) and acquirer and target projects (panel B). The treated projects are compared to the set of all never treated projects. The underlying regression has the following form:

$$Outcome_ip = \beta_0 p + \beta_1 pTreated_i p + \beta_2 pFE_i p + \epsilon_i p,$$

where observation i corresponds to a project-phase and p represents the acquiror (A), target (T), or all $(A+T)$ project sets, respectively. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D4: Average effects (logit)

Panel A: All

	All		
	(1)	(2)	(3)
	Termination	Progress	New Patents
Treated	0.836***	-0.659***	-1.341***
	(0.160)	(0.141)	(0.181)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	1935	2005	1935
Pseudo R2	0.116	0.111	0.204

Marginal effects

	All		
	(1)	(2)	(3)
	Termination	Progress	New Patents
Treated	0.092***	-0.137***	-0.237***
	(0.017)	(0.029)	(0.030)

Panel B: Acquirers and targets

	Acquirer			Target		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
Treated	0.101	-0.170	-1.055***	1.374***	-1.244***	-1.722***
	(0.247)	(0.179)	(0.245)	(0.196)	(0.221)	(0.260)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1784	1853	1784	1768	1838	1768
Pseudo R2	0.098	0.109	0.205	0.136	0.114	0.227

Marginal effects

	Acquirer			Target		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
Treated	0.010	-0.036	-0.189***	0.146***	-0.258***	-0.297***
	(0.024)	(0.038)	(0.042)	(0.020)	(0.045)	(0.042)

Notes: This table shows the results of the logit regressions measuring the effect of M&A on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D5: R&D and market incumbency

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.286***	-0.256***	-0.344***
	(0.054)	(0.043)	(0.039)
R&D Inc	0.092**	-0.101**	-0.273***
	(0.047)	(0.049)	(0.047)
Product Market Inc	-0.073***	0.077***	-0.082***
	(0.015)	(0.028)	(0.025)
R&D Inc × Product Market Inc	-0.015	-0.013	0.160**
	(0.056)	(0.066)	(0.065)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.100	0.132	0.246

Panel B: Acquirers and targets

	Acquirer's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.285***	-0.251***	-0.343***
				(0.053)	(0.043)	(0.039)
R&D Inc	0.022	-0.007	-0.270***	0.182**	-0.212***	-0.279***
	(0.055)	(0.066)	(0.057)	(0.075)	(0.067)	(0.076)
Product Market Inc	-0.076***	0.079***	-0.081***	-0.075***	0.080***	-0.089***
	(0.015)	(0.029)	(0.025)	(0.015)	(0.029)	(0.025)
R&D Inc × Product Market Inc	0.039	-0.086	0.169**	-0.029	-0.006	0.106
	(0.064)	(0.081)	(0.076)	(0.113)	(0.112)	(0.112)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	1838
Adj. R2	0.061	0.125	0.249	0.107	0.131	0.271

Notes: This table shows the results of the OLS regressions measuring the effect of M&As depending on R&D and market incumbency status on all projects (panel A) and acquirer and target projects (panel B). The treated projects are split in three exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D6: Technological closeness and MoA overlap

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.301***	-0.272***	-0.325***
	(0.053)	(0.043)	(0.038)
R&D Inc rest	0.068**	-0.075**	-0.230***
	(0.029)	(0.033)	(0.034)
R&D Inc + Twin + MoA	-0.035	-0.141	0.013
	(0.058)	(0.094)	(0.085)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.094	0.129	0.244

Panel B: Acquirers and targets

	Acquirer's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.301***	-0.268***	-0.324***
				(0.053)	(0.043)	(0.038)
R&D Inc rest	0.021	-0.018	-0.197***	0.203***	-0.233***	-0.329***
	(0.030)	(0.039)	(0.040)	(0.066)	(0.056)	(0.058)
R&D Inc + Twin + MoA	-0.033	-0.224*	-0.065	-0.039	-0.058	0.084
	(0.082)	(0.118)	(0.097)	(0.082)	(0.140)	(0.133)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	1838
Adj. R2	0.053	0.123	0.245	0.103	0.128	0.270

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness and MoA overlap on all projects (panel A) and on acquirer's and target projects (panel B). The treated projects are split in three exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D7: Tech closeness, MoA overlap, R&D and market incumbency

Panel A: Combined

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.286***	-0.256***	-0.343***
	(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.105**	-0.068	-0.279***
	(0.050)	(0.052)	(0.051)
R&D Inc + Twin + MoA	0.007	-0.330***	-0.234**
	(0.118)	(0.120)	(0.102)
Prod Mkt Inc	-0.074***	0.077***	-0.080***
	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	-0.015	-0.059	0.127*
	(0.061)	(0.069)	(0.069)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.057	0.330**	0.493***
	(0.120)	(0.167)	(0.145)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.100	0.133	0.250

Panel B: Acquirers and targets

	Acquirer's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.285***	-0.251***	-0.343***
				(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.027	0.024	-0.267***	0.207***	-0.176**	-0.298***
	(0.059)	(0.070)	(0.065)	(0.080)	(0.071)	(0.079)
R&D Inc + Twin + MoA	-0.008	-0.207	-0.294***	0.006	-0.480***	-0.151
	(0.148)	(0.172)	(0.053)	(0.194)	(0.112)	(0.224)
Prod Mkt Inc	-0.076***	0.078***	-0.079***	-0.076***	0.081***	-0.087***
	(0.015)	(0.029)	(0.025)	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	0.040	-0.108	0.147*	0.022	-0.206*	-0.054
	(0.068)	(0.085)	(0.083)	(0.138)	(0.111)	(0.100)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.038	-0.054	0.506***	-0.045	0.681***	0.432
	(0.151)	(0.235)	(0.153)	(0.195)	(0.169)	(0.264)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	1838
Adj. R2	0.060	0.125	0.250	0.109	0.135	0.275

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Robust standard errors in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D8: Robustness - Tech closeness, MoA overlap, R&D and market incumbency with pooled matching

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.201***	-0.162***	-0.287***
	(0.065)	(0.059)	(0.054)
R&D Inc + rest	0.018	0.027	-0.176***
	(0.060)	(0.065)	(0.062)
R&D Inc + Twin + MoA	-0.027	-0.228*	-0.056
	(0.105)	(0.130)	(0.115)
Prod Mkt Inc	-0.122***	0.217***	-0.069
	(0.035)	(0.055)	(0.048)
R&D Inc + rest × Prod Mkt Inc	0.080	-0.153*	0.162**
	(0.069)	(0.084)	(0.078)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.094	0.257	0.560***
	(0.118)	(0.177)	(0.172)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	638	638	638
Adj. R2	0.167	0.276	0.197

Panel B: Acquirers and targets

	Acquirer's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.152**	-0.116*	-0.238***
				(0.075)	(0.070)	(0.062)
R&D Inc + rest	0.026	-0.002	-0.259***	0.089	-0.074	-0.148
	(0.080)	(0.094)	(0.093)	(0.093)	(0.093)	(0.095)
R&D Inc + Twin + MoA	0.025	-0.117	-0.201**	-0.051	-0.377***	0.118
	(0.138)	(0.152)	(0.101)	(0.179)	(0.116)	(0.255)
Prod Mkt Inc	-0.061	0.166**	-0.137**	-0.193***	0.261***	0.089
	(0.046)	(0.081)	(0.066)	(0.061)	(0.089)	(0.082)
R&D Inc + rest × Prod Mkt Inc	0.061	-0.085	0.297***	0.140	-0.305**	-0.206
	(0.079)	(0.116)	(0.103)	(0.150)	(0.150)	(0.138)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.146	-0.175	0.744***	-0.019	0.589***	0.156
	(0.160)	(0.213)	(0.195)	(0.197)	(0.192)	(0.305)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	334	334	334	304	304	304
Adj. R2	0.128	0.341	0.199	0.208	0.255	0.261

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the pooled counterfactual group, consisting of the technologically most similar, never treated projects of other firms in the same phase, assigned to each treated project. The underlying regression has the same form as Table D1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D9: Robustness: Tech closeness, MoA overlap, R&D and market incumbency with exact matching

Panel A: Combined

	All projects		
	(1)	(2)	(3)
	Progress	Termination	New Patents
R&D non-Inc	0.286***	-0.162**	-0.273***
	(0.071)	(0.077)	(0.063)
R&D Inc + rest	0.043	-0.048	-0.180**
	(0.078)	(0.079)	(0.080)
R&D Inc + Twin + MoA	-0.087	-0.066	0.068
	(0.162)	(0.200)	(0.170)
Prod Mkt Inc	-0.054	0.129*	-0.059
	(0.064)	(0.075)	(0.063)
R&D Inc + rest × Prod Mkt Inc	0.024	-0.125	0.100
	(0.099)	(0.112)	(0.104)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.250	0.161	0.246
	(0.216)	(0.260)	(0.215)
MoA FE	Yes	Yes	Yes
Cohort	Yes	Yes	Yes
Stage	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Match pair FE	Yes	Yes	Yes
Obs	638	638	638
Adj. R2	0.222	0.349	0.295

Panel B: Acquirers and targets

	Acquiror's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Progress	Termination	New Patents	Progress	Termination	New Patents
R&D non-Inc				0.241**	-0.166	-0.289***
				(0.095)	(0.105)	(0.068)
R&D Inc + rest	0.098	-0.020	-0.237*	0.038	-0.151	-0.182
	(0.090)	(0.108)	(0.136)	(0.130)	(0.137)	(0.111)
R&D Inc + Twin + MoA	-0.003	0.182	-0.229	-0.179	-0.339	0.148
	(0.111)	(0.223)	(0.142)	(0.377)	(0.275)	(0.413)
Prod Mkt Inc	0.036	0.118	-0.068	-0.123	0.160	-0.072
	(0.079)	(0.107)	(0.092)	(0.133)	(0.156)	(0.118)
R&D Inc + rest × Prod Mkt Inc	-0.089	-0.080	0.150	0.062	-0.228	-0.075
	(0.112)	(0.146)	(0.150)	(0.218)	(0.236)	(0.211)
R&D Inc + Twin + MoA × Prod Mkt Inc	0.025	-0.573*	0.843**	-0.271	0.687*	-0.059
	(0.170)	(0.340)	(0.327)	(0.419)	(0.356)	(0.420)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Match pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	334	334	334	304	304	304
Adj. R2	0.232	0.437	0.261	0.175	0.190	0.367

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness and MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to their counterfactual counterparts (ie matched never treated technologically closest project of other firms in the same phase). The underlying regression has the same form as Table D1. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D10: Robustness - Tech closeness, MoA overlap, R&D and market incumbency (clustering at firm level)

Panel A: Combined

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.286***	-0.256***	-0.343***
	(0.054)	(0.047)	(0.041)
R&D Inc + rest	0.105*	-0.068	-0.279***
	(0.055)	(0.048)	(0.045)
R&D Inc + Twin + MoA	0.007	-0.330**	-0.234**
	(0.173)	(0.135)	(0.104)
Prod Mkt Inc	-0.074***	0.077**	-0.080**
	(0.017)	(0.030)	(0.036)
R&D Inc + rest × Prod Mkt Inc	-0.015	-0.059	0.127*
	(0.062)	(0.062)	(0.076)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.057	0.330*	0.493**
	(0.176)	(0.169)	(0.210)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.100	0.133	0.250

Panel B: Acquirers and targets

	Acquiror's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.285***	-0.251***	-0.343***
				(0.054)	(0.047)	(0.041)
R&D Inc + rest	0.027	0.024	-0.267***	0.207**	-0.176***	-0.298***
	(0.071)	(0.071)	(0.066)	(0.083)	(0.062)	(0.083)
R&D Inc + Twin + MoA	-0.008	-0.207	-0.294***	0.006	-0.480***	-0.151
	(0.163)	(0.169)	(0.075)	(0.201)	(0.122)	(0.208)
Prod Mkt Inc	-0.076***	0.078***	-0.079**	-0.076***	0.081***	-0.087**
	(0.016)	(0.029)	(0.037)	(0.017)	(0.030)	(0.037)
R&D Inc + rest × Prod Mkt Inc	0.040	-0.108	0.147	0.022	-0.206**	-0.054
	(0.078)	(0.084)	(0.098)	(0.129)	(0.095)	(0.094)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.038	-0.054	0.506***	-0.045	0.681***	0.432
	(0.168)	(0.214)	(0.165)	(0.202)	(0.153)	(0.298)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	1838
Adj. R2	0.060	0.125	0.250	0.109	0.135	0.275

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D11: Robustness - Tech closeness, MoA overlap, R&D and market incumbency (clustering at transaction level)

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.201***	-0.162**	-0.287***
	(0.066)	(0.062)	(0.052)
R&D Inc + rest	0.018	0.027	-0.176***
	(0.056)	(0.063)	(0.060)
R&D Inc + Twin + MoA	-0.027	-0.228*	-0.056
	(0.143)	(0.129)	(0.098)
Mkt Inc	-0.122***	0.217***	-0.069
	(0.035)	(0.051)	(0.050)
R&D Inc + rest × Mkt Inc	0.080	-0.153*	0.162*
	(0.062)	(0.086)	(0.096)
R&D Inc + Twin + MoA × Mkt Inc	-0.094	0.257	0.560***
	(0.165)	(0.174)	(0.204)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	638	638	638
Adj. R2	0.167	0.276	0.197

Panel B: Acquirers and targets

	Acquiror's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.152*	-0.116	-0.238***
				(0.080)	(0.079)	(0.063)
R&D Inc + rest	0.026	-0.002	-0.259**	0.089	-0.074	-0.148
	(0.076)	(0.084)	(0.097)	(0.094)	(0.094)	(0.093)
R&D Inc + Twin + MoA	0.025	-0.117	-0.201**	-0.051	-0.377***	0.118
	(0.144)	(0.137)	(0.075)	(0.191)	(0.120)	(0.257)
Mkt Inc	-0.061	0.166**	-0.137**	-0.193***	0.261***	0.089
	(0.054)	(0.074)	(0.066)	(0.064)	(0.091)	(0.081)
R&D Inc + rest × Mkt Inc	0.061	-0.085	0.297**	0.140	-0.305*	-0.206
	(0.075)	(0.115)	(0.142)	(0.155)	(0.161)	(0.129)
R&D Inc + Twin + MoA × Mkt Inc	-0.146	-0.175	0.744***	-0.019	0.589***	0.156
	(0.171)	(0.177)	(0.133)	(0.215)	(0.199)	(0.323)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	334	334	334	304	304	304
Adj. R2	0.128	0.341	0.199	0.208	0.255	0.261

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the pooled counterfactual group, consisting of the technologically most similar, never treated projects of other firms in the same phase, assigned to each treated project. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D12: Robustness - Tech closeness, MoA overlap, R&D and market incumbency for non-terminated projects only

Panel A: All

	All projects	
	(1)	(2)
	Progress	New Patents
R&D non-Inc	-0.201***	-0.253***
	(0.069)	(0.055)
R&D Inc + rest	-0.018	-0.261***
	(0.063)	(0.057)
R&D Inc + Twin + MoA	-0.301**	-0.159
	(0.127)	(0.110)
Prod Mkt Inc	0.036	-0.078***
	(0.030)	(0.025)
R&D Inc + rest × Prod Mkt Inc	-0.067	0.124
	(0.080)	(0.078)
R&D Inc + Twin + MoA × Prod Mkt Inc	0.260	0.430***
	(0.174)	(0.152)
MoA FE	Yes	Yes
Cohort FE	Yes	Yes
Stage FE	Yes	Yes
Pat stock FE	Yes	Yes
Obs	1730	1730
Adj. R2	0.130	0.255

Panel B: Acquirers and targets

	Acquiror's projects		Target projects	
	(1)	(2)	(3)	(4)
	Progress	New Patents	Progress	New Patents
R&D non-Inc			-0.195***	-0.249***
			(0.069)	(0.055)
R&D Inc + rest	0.036	-0.247***	-0.102	-0.293***
	(0.077)	(0.072)	(0.102)	(0.094)
R&D Inc + Twin + MoA	-0.162	-0.261***	-0.479***	-0.013
	(0.169)	(0.056)	(0.086)	(0.227)
Prod Mkt Inc	0.038	-0.078***	0.042	-0.089***
	(0.030)	(0.025)	(0.030)	(0.025)
R&D Inc + rest × Prod Mkt Inc	-0.081	0.145	-0.303*	-0.133
	(0.093)	(0.091)	(0.159)	(0.116)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.141	0.489***	0.645***	0.313
	(0.235)	(0.156)	(0.155)	(0.268)
MoA FE	Yes	Yes	Yes	Yes
Cohort	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes
Obs	1638	1638	1589	1589
Adj. R2	0.131	0.255	0.127	0.284

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the set of all never treated projects. Terminated projects (both treated and controls) are excluded from the analysis. This restrict the outcome variables to *Progression* and *New Patents* only. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D13: Robustness - Tech closeness, MoA overlap, R&D and market incumbency with Phase III included

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.297***	-0.243***	-0.341***
	(0.053)	(0.044)	(0.038)
R&D Inc + rest	0.101**	-0.065	-0.289***
	(0.049)	(0.051)	(0.050)
R&D Inc + Twin + MoA	0.007	-0.330***	-0.231**
	(0.118)	(0.120)	(0.100)
Prod Mkt Inc	-0.073***	0.072**	-0.074***
	(0.015)	(0.028)	(0.025)
R&D Inc + rest × Prod Mkt Inc	-0.016	-0.015	0.091
	(0.058)	(0.068)	(0.067)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.054	0.369**	0.425***
	(0.120)	(0.167)	(0.153)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2028	2028	2028
Adj. R2	0.103	0.132	0.238

Panel B: Acquirers and targets

	Acquirer's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.296***	-0.238***	-0.342***
				(0.053)	(0.044)	(0.038)
R&D Inc + rest	0.023	0.024	-0.283***	0.209***	-0.175**	-0.299***
	(0.056)	(0.068)	(0.064)	(0.080)	(0.071)	(0.079)
R&D Inc + Twin + MoA	-0.007	-0.209	-0.290***	0.006	-0.476***	-0.153
	(0.148)	(0.173)	(0.050)	(0.192)	(0.110)	(0.224)
Prod Mkt Inc	-0.076***	0.074***	-0.073***	-0.076***	0.081***	-0.087***
	(0.015)	(0.029)	(0.025)	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	0.043	-0.066	0.112	0.011	-0.145	-0.074
	(0.064)	(0.082)	(0.081)	(0.133)	(0.122)	(0.099)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.038	-0.059	0.512***	-0.041	0.728***	0.302
	(0.151)	(0.234)	(0.151)	(0.194)	(0.163)	(0.283)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1871	1871	1871	1843	1843	1843
Adj. R2	0.061	0.127	0.238	0.110	0.132	0.273

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the set of all never treated projects. All Phase III projects are included in the sample. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D14: Robustness - Effects of M&A: Technological closeness, MoA overlap, and product market incumbency with control for non-diabetic patents

Panel A: Combined

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.284***	-0.259***	-0.345***
	(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.107**	-0.063	-0.277***
	(0.050)	(0.052)	(0.051)
R&D Inc + Twin + MoA	0.006	-0.332***	-0.235**
	(0.119)	(0.119)	(0.102)
Prod Mkt Inc	-0.051***	0.120***	-0.059*
	(0.019)	(0.034)	(0.030)
R&D Inc + rest × Prod Mkt Inc	-0.017	-0.064	0.124*
	(0.060)	(0.069)	(0.069)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.070	0.304*	0.481***
	(0.121)	(0.165)	(0.145)
Pat NoDiab	-0.000*	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
MoA FE	Yes	Yes	Yes
Cohort	Yes	Yes	Yes
Stage	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.101	0.135	0.250

Panel B: Acquirers and targets

	Acquirer's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.283***	-0.255***	-0.346***
				(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.030	0.034	-0.262***	0.207***	-0.176**	-0.297***
	(0.059)	(0.070)	(0.065)	(0.080)	(0.071)	(0.079)
R&D Inc + Twin + MoA	-0.009	-0.211	-0.296***	0.007	-0.477***	-0.149
	(0.148)	(0.171)	(0.053)	(0.195)	(0.110)	(0.223)
Prod Mkt Inc	-0.059***	0.131***	-0.050	-0.055***	0.130***	-0.049
	(0.018)	(0.035)	(0.031)	(0.018)	(0.037)	(0.032)
R&D Inc + rest × Prod Mkt Inc	0.040	-0.109	0.146*	-0.000	-0.257**	-0.095
	(0.068)	(0.085)	(0.083)	(0.138)	(0.113)	(0.102)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.039	-0.057	0.504***	-0.070	0.625***	0.388
	(0.151)	(0.236)	(0.154)	(0.196)	(0.169)	(0.264)
Pat NoDiab	-0.000	-0.000**	-0.000	-0.000*	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	1838
Adj. R2	0.060	0.128	0.250	0.109	0.137	0.276

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D15: Robustness - Effects of M&A: Technological closeness, MoA overlap, and product market incumbency on sample with core diabetes transactions (matched counterfactuals)

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.141*	-0.140**	-0.250***
	(0.076)	(0.070)	(0.062)
R&D Inc + rest	-0.005	-0.013	-0.179**
	(0.066)	(0.074)	(0.069)
R&D Inc + Twin + MoA	-0.073	-0.187	-0.016
	(0.095)	(0.128)	(0.117)
Prod Mkt Inc	-0.153***	0.186***	-0.061
	(0.037)	(0.065)	(0.054)
R&D Inc + rest × Prod Mkt Inc	0.118	-0.146	0.191**
	(0.078)	(0.097)	(0.086)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.002	0.283	0.526***
	(0.112)	(0.183)	(0.188)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	494	494	494
Adj. R2	0.163	0.308	0.227

Panel B: Acquirers and targets

	Acquiror's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.114	-0.096	-0.171**
				(0.090)	(0.085)	(0.071)
R&D Inc + rest	-0.030	-0.081	-0.265***	0.077	-0.110	-0.111
	(0.088)	(0.109)	(0.100)	(0.105)	(0.109)	(0.108)
R&D Inc + Twin + MoA	-0.077	0.000	-0.172	-0.083	-0.399***	0.140
	(0.089)	(0.149)	(0.114)	(0.214)	(0.131)	(0.254)
Prod Mkt Inc	-0.110**	0.202**	-0.155**	-0.209**	0.144	0.113
	(0.045)	(0.090)	(0.070)	(0.083)	(0.102)	(0.098)
R&D Inc + rest × Prod Mkt Inc	0.141	-0.109	0.354***	0.077	-0.201	-0.238
	(0.088)	(0.128)	(0.105)	(0.180)	(0.171)	(0.170)
R&D Inc + Twin + MoA × Prod Mkt Inc	0.087	-0.296	0.750***	-0.064	0.740***	0.067
	(0.116)	(0.206)	(0.218)	(0.248)	(0.221)	(0.318)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	266	266	266	228	228	228
Adj. R2	0.133	0.396	0.308	0.165	0.259	0.307

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D16: Robustness - Tech closeness, MoA overlap, R&D and market incumbency with citation closeness measure

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.286***	-0.256***	-0.343***
	(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.083*	-0.094*	-0.271***
	(0.046)	(0.049)	(0.047)
R&D Inc + MoA + Cit	0.898***	-0.735***	-0.432***
	(0.046)	(0.069)	(0.061)
Prod Mkt Inc	-0.073***	0.077***	-0.081***
	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	-0.004	-0.024	0.143**
	(0.057)	(0.066)	(0.066)
R&D Inc + MoA + Cit × Prod Mkt Inc	-0.891***	0.710***	0.702***
	(0.051)	(0.179)	(0.088)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.102	0.132	0.247

Panel B: Acquirers and targets

	Acquiror's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.285***	-0.251***	-0.343***
				(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.003	0.009	-0.266***	0.182**	-0.211***	-0.279***
	(0.053)	(0.065)	(0.058)	(0.075)	(0.067)	(0.076)
R&D Inc + MoA + Cit	0.901***	-0.784***	-0.461***	-0.000	0.276***	0.212***
	(0.045)	(0.072)	(0.065)	(0.031)	(0.059)	(0.077)
Prod Mkt Inc	-0.076***	0.079***	-0.079***	-0.075***	0.081***	-0.088***
	(0.015)	(0.029)	(0.025)	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	0.059	-0.098	0.154**	-0.015	-0.051	0.071
	(0.063)	(0.081)	(0.077)	(0.118)	(0.114)	(0.114)
R&D Inc + MoA + Cit × Prod Mkt Inc	-0.889***	0.556**	0.738***			
	(0.055)	(0.218)	(0.114)			
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	1838
Adj. R2	0.064	0.126	0.249	0.107	0.132	0.271

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness (citations), MoA overlap, R&D and product market incumbency on all projects (panel A) and acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D17: Robustness - Tech closeness, MoA overlap, R&D and market incumbency with Jaffe closeness measure

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc (Jaffe)	0.273***	-0.253***	-0.342***
	(0.054)	(0.044)	(0.039)
R&D Inc + rest (Jaffe)	0.103**	-0.087*	-0.271***
	(0.048)	(0.050)	(0.048)
R&D Inc+MoA+Twin (Jaffe)	0.188	-0.408***	-0.353***
	(0.205)	(0.131)	(0.083)
Prod Mkt Inc	-0.073***	0.077***	-0.080***
	(0.015)	(0.029)	(0.025)
R&D Inc + rest (Jaffe) × Prod Mkt Inc	-0.013	-0.045	0.123*
	(0.059)	(0.068)	(0.067)
R&D Inc+MoA+Twin (Jaffe) × Prod Mkt Inc	-0.240	0.465***	0.594***
	(0.207)	(0.173)	(0.139)
MoA FE	Yes	Yes	Yes
Cohort	Yes	Yes	Yes
Stage	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.098	0.133	0.249

Panel B: Acquirers and targets

	Acquiror's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc (Jaffe)				0.272***	-0.249***	-0.342***
				(0.054)	(0.044)	(0.040)
R&D Inc + rest (Jaffe)	0.018	0.015	-0.273***	0.207***	-0.199***	-0.272***
	(0.055)	(0.069)	(0.061)	(0.076)	(0.064)	(0.075)
R&D Inc+MoA+Twin (Jaffe)	0.069	-0.283*	-0.242***	0.364	-0.645***	-0.553***
	(0.254)	(0.159)	(0.080)	(0.349)	(0.169)	(0.130)
Prod Mkt Inc	-0.076***	0.079***	-0.080***	-0.076***	0.081***	-0.088***
	(0.015)	(0.029)	(0.025)	(0.015)	(0.029)	(0.025)
R&D Inc + rest (Jaffe) × Prod Mkt Inc	0.048	-0.105	0.159**	0.021	-0.184*	-0.079
	(0.065)	(0.084)	(0.080)	(0.135)	(0.106)	(0.096)
R&D Inc+MoA+Twin (Jaffe) × Prod Mkt Inc	-0.121	0.112	0.402**	-0.402	0.846***	0.833***
	(0.257)	(0.231)	(0.183)	(0.350)	(0.209)	(0.190)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	1838
Adj. R2	0.060	0.125	0.249	0.107	0.135	0.275

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness (Jaffe), MoA overlap, R&D and product market incumbency on all projects (panel A) and on acquirer's and target projects (panel B). The treated projects are split in five exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D18: Robustness - Tech closeness, MoA overlap, R&D and market incumbency - alternative twin cutoff (p90)

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.286***	-0.256***	-0.343***
	(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.107**	-0.063	-0.279***
	(0.051)	(0.052)	(0.051)
R&D Inc + Twin + MoA	0.000	-0.344***	-0.241**
	(0.109)	(0.112)	(0.095)
Prod Mkt Inc	-0.074***	0.076***	-0.080***
	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	-0.023	-0.056	0.126*
	(0.061)	(0.070)	(0.070)
R&D Inc + Twin + MoA × Prod Mkt Inc	0.019	0.261	0.450***
	(0.128)	(0.161)	(0.134)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.100	0.133	0.249

Panel B: Acquirers and targets

	Acquirer's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.285***	-0.252***	-0.343***
				(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.029	0.035	-0.266***	0.207***	-0.177**	-0.279***
	(0.060)	(0.070)	(0.066)	(0.080)	(0.071)	(0.051)
R&D Inc + Twin + MoA	-0.018	-0.241	-0.295***	0.006	-0.480***	-0.241**
	(0.130)	(0.154)	(0.048)	(0.194)	(0.112)	(0.095)
Prod Mkt Inc	-0.076***	0.078***	-0.079***	-0.076***	0.081***	-0.080***
	(0.015)	(0.029)	(0.025)	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	0.038	-0.119	0.146*	-0.005	-0.180	0.126*
	(0.069)	(0.086)	(0.084)	(0.141)	(0.117)	(0.070)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.028	-0.021	0.507***	0.062	0.506***	0.450***
	(0.133)	(0.222)	(0.152)	(0.220)	(0.185)	(0.134)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	2005
Adj. R2	0.060	0.126	0.250	0.108	0.133	0.249

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and on acquirer's and target projects (panel B). The *twin* definition differs from the baseline and corresponds to threshold of the 90th percentile of all-pairs similarity distribution. The treated projects are split in five exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tab. D19: Robustness - Tech closeness, MoA overlap, R&D and market incumbency - alternative twin cutoff (p99)

Panel A: All

	All projects		
	(1)	(2)	(3)
	Termination	Progress	New Patents
R&D non-Inc	0.286***	-0.256***	-0.343***
	(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.088*	-0.071	-0.263***
	(0.048)	(0.051)	(0.049)
R&D Inc + Twin + MoA	0.152	-0.493***	-0.410***
	(0.173)	(0.103)	(0.067)
Prod Mkt Inc	-0.073***	0.076***	-0.080***
	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	0.002	-0.053	0.114*
	(0.059)	(0.068)	(0.068)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.206	0.469***	0.664***
	(0.175)	(0.161)	(0.130)
MoA FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes
Obs	2005	2005	2005
Adj. R2	0.100	0.134	0.249

Panel B: Acquirers and targets

	Acquirer's projects			Target projects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Termination	Progress	New Patents	Termination	Progress	New Patents
R&D non-Inc				0.285***	-0.251***	-0.343***
				(0.054)	(0.043)	(0.039)
R&D Inc + rest	0.015	0.024	-0.267***	0.183**	-0.182***	-0.263***
	(0.056)	(0.068)	(0.061)	(0.078)	(0.068)	(0.049)
R&D Inc + Twin + MoA	0.104	-0.386***	-0.308***	0.188	-0.617***	-0.410***
	(0.235)	(0.150)	(0.076)	(0.271)	(0.116)	(0.067)
Prod Mkt Inc	-0.076***	0.078***	-0.079***	-0.076***	0.081***	-0.080***
	(0.015)	(0.029)	(0.025)	(0.015)	(0.029)	(0.025)
R&D Inc + rest × Prod Mkt Inc	0.052	-0.108	0.148*	0.034	-0.165	0.114*
	(0.065)	(0.083)	(0.080)	(0.132)	(0.111)	(0.068)
R&D Inc + Twin + MoA × Prod Mkt Inc	-0.149	0.125	0.521***	-0.235	0.806***	0.664***
	(0.237)	(0.219)	(0.163)	(0.272)	(0.186)	(0.130)
MoA FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Pat stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1853	1853	1853	1838	1838	2005
Adj. R2	0.060	0.126	0.250	0.108	0.135	0.249

Notes: This table shows the results of the OLS regressions measuring the effect of M&A depending on the combination of technological closeness, MoA overlap, R&D and product market incumbency on all projects (panel A) and on acquirer's and target projects (panel B). The *twin* definition differs from the baseline and corresponds to threshold of the 99th percentile of all-pairs similarity distribution. The treated projects are split in five exclusive groups and compared to the set of all never treated projects. The underlying regression has the same form as Table D1. Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix E: Comparison with Cunningham et al. (2021)

We present numbers aimed at comparing our work to those presented in Cunningham et. al (2021). In Cunningham et. al (2021), overlap is defined for target projects if the acquiring firm owns a launched project and the target owns a project under development in the same specific therapeutic area and same MoA.

In the table below, we present all numbers (absolute and percentages) on the MoA overlap between acquirer and target projects in our sample. There are 1686 target projects that are not acquired and 157 that are acquired (our treated target projects; see row (2)). One can slice these projects in different ways, as we do in this paper. Row (4) shows that 16 treated target projects have overlap with the acquirer (an, hence, 141 do not; see row (3))). Row (6) then shows that of these 16 target projects with MoA overlap, 11 were taken over by an acquirer that was also a product market incumbent (row (6)). Row (8) then, finally, shows that out of these 11 target projects with MoA overlap, 2 had overlap with launched products of the acquiring product market incumbent. It is this last category that is identical to the overlap that Cunningham et al. (2021) define. These are not enough observations for any statistical analysis.

Tab. E1: Description of Project Acquisitions

		N	Share
	Full sample (Targets)	1843	100%
(1)	Non-acquired	1686	91.5%
(2)	Acquired [(3)+(4)]	157	8.5%
(3)	Acquired: No MoA overlap	141	7.7%
(4)	Acquired: MoA overlap [(5) + (6)]	16	0.8%
(5)	Acquired: MoA overlap and acquirer not product market incumbent	5	0.3%
(6)	Acquired: MoA overlap and acquirer product market incumbent [(7) + (8)]	11	0.5%
(7)	Acquired: MoA overlap with R&D project of acquirer product market incumbent	9	0.4%
(8)	Acquired: MoA overlap with launched product of acquirer product market incumbent	2	0.1%

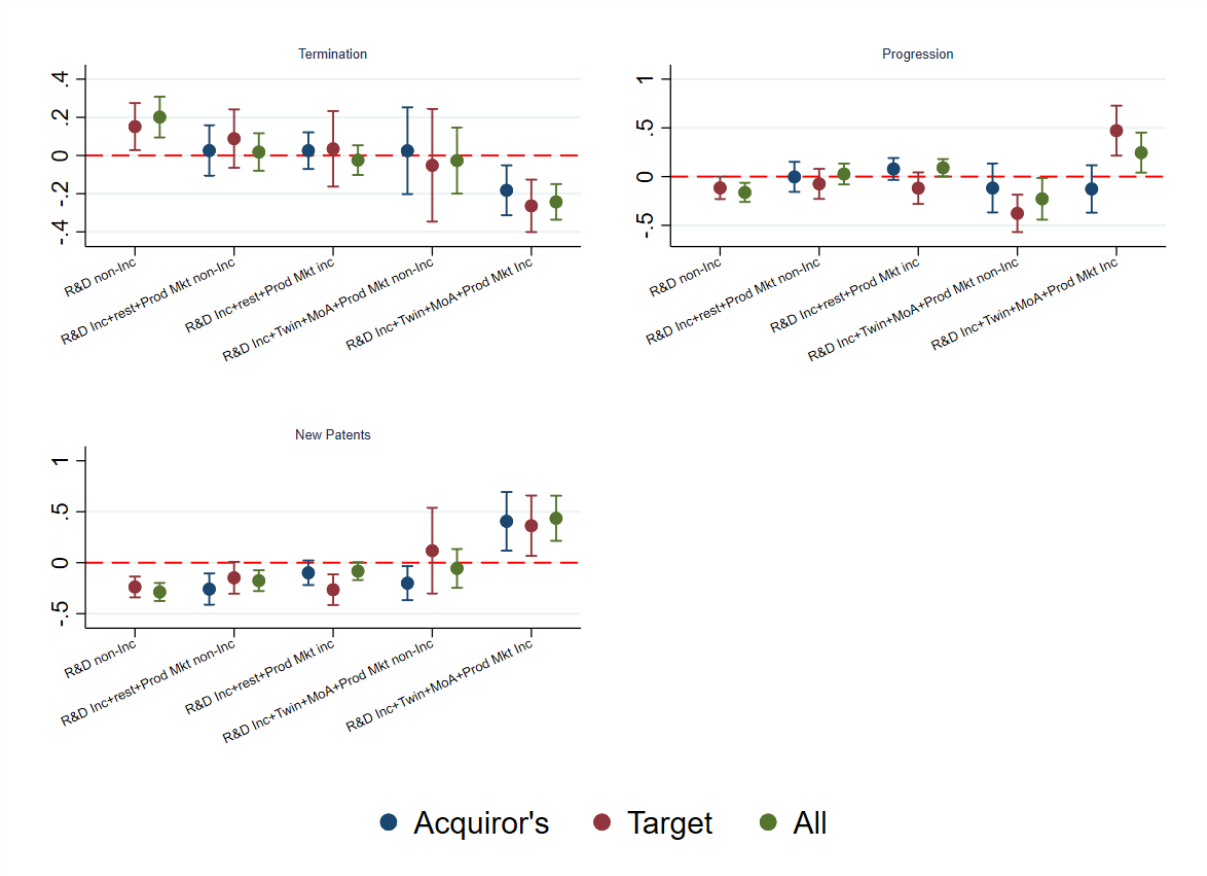
Appendix F: Phase III acquired projects

Tab. F1: Projects treated in Phase III: identity of firms and key information

Transaction	ID	Date	Acquirer	Target	Progression	Termination	New Patents	Acquirer product market incumbent	R&D non-incumbent	Twin	Sibling	MoA overlap
Target	17	7/1/2012	glaxosmithkline	human genome sc	1	0	0	1	0	1	0	1
Target	40	1/1/2011	sanofi	genzyme	1	0	0	1	0	0	1	0
Target	205	7/1/2007	andromeda bio	develogen	0	1	0	0	1	0	0	0
Target	227	1/1/2014	hyperion	andromeda bio	0	1	0	0	1	0	0	0
Target	275	1/1/2006	veroscience	pliva	1	0	1	0	1	0	0	0
Acquirer	8	1/1/2013	biocon		0	0	0	0	0	0	1	0
Acquirer	10	7/1/2012	bristol-myers squibb		1	0	0	1	0	1	0	0
Acquirer	16	1/1/2008	glaxosmithkline		0	0	1	1	0	1	0	0
Acquirer	24	7/1/2006	merck & co.		1	0	0	1	0	0	1	0
Acquirer	24	7/1/2006	merck & co.		1	0	0	1	0	0	1	0
Acquirer	25	1/1/2011	merck & co.		1	0	0	1	0	1	0	0
Acquirer	25	1/1/2011	merck & co.		1	0	0	1	0	1	0	0
Acquirer	29	7/1/2005	nektar therapeutics		1	0	0	0	0	0	1	1
Acquirer	31	7/1/2008	novo nordisk		1	0	0	1	0	0	1	0
Acquirer	31	7/1/2008	novo nordisk		1	0	0	1	0	0	1	0
Acquirer	39	1/1/2011	roche		0	0	1	1	0	0	1	0
Acquirer	47	1/1/2005	takeda		1	0	1	1	0	1	0	0
Acquirer	47	1/1/2005	takeda		0	0	0	1	0	1	0	0
Acquirer	47	1/1/2005	takeda		1	0	0	1	0	0	1	0
Acquirer	48	1/1/2011	takeda		1	0	0	1	0	1	0	0
Acquirer	48	1/1/2011	takeda		1	0	0	1	0	1	0	0
Acquirer	48	1/1/2011	takeda		1	0	0	1	0	1	0	0
Acquirer	48	1/1/2011	takeda		0	0	1	1	0	1	0	0

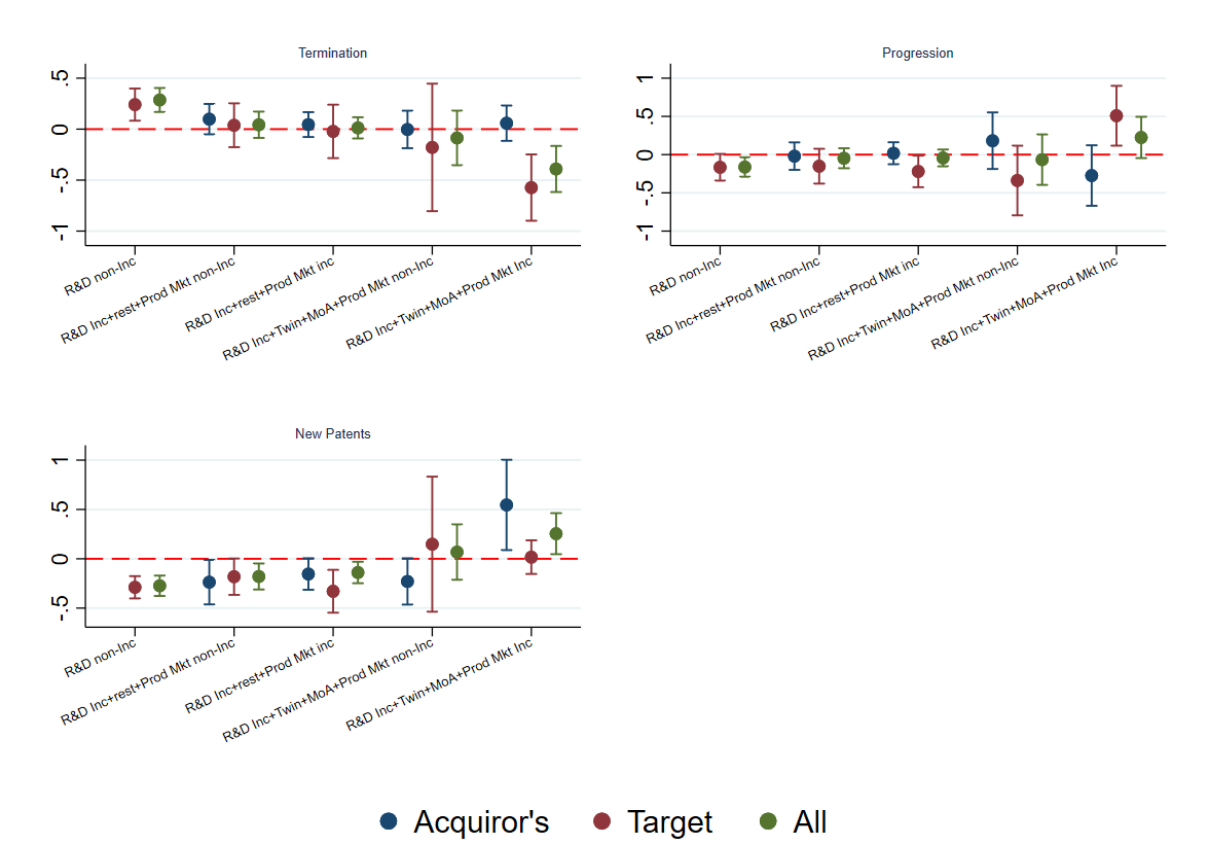
Appendix G: Figures of robustness checks

Fig. G1: Robustness - Effects of M&As - Pooled matching



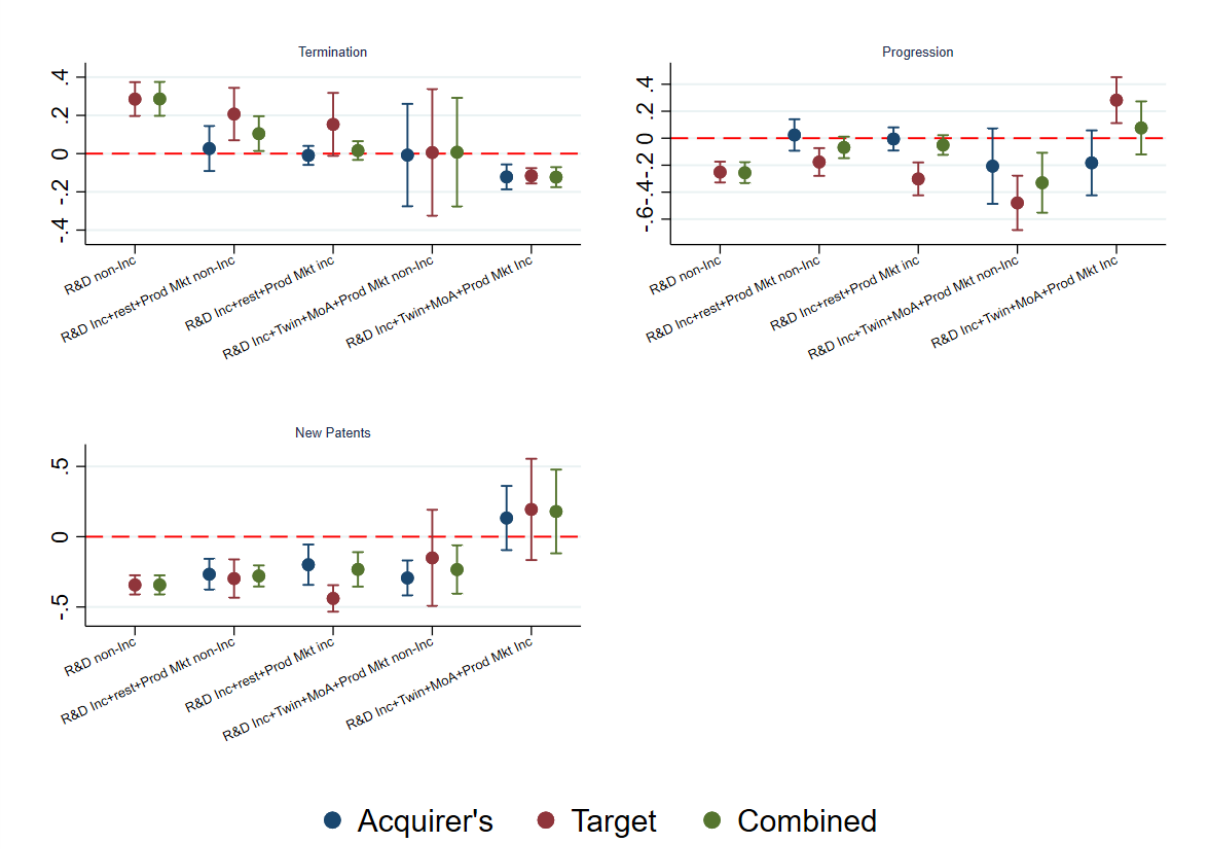
Note: This figure visualizes the estimated effects of M&As depending on the combination of technological closeness, MoA overlap, and market incumbency compared to the pooled group of never treated counterfactuals (same phase and technologically closest projects from other companies). We report robust standard errors. Full regression results are presented in table D8.

Fig. G2: Robustness - Effects of M&As - Exact matching



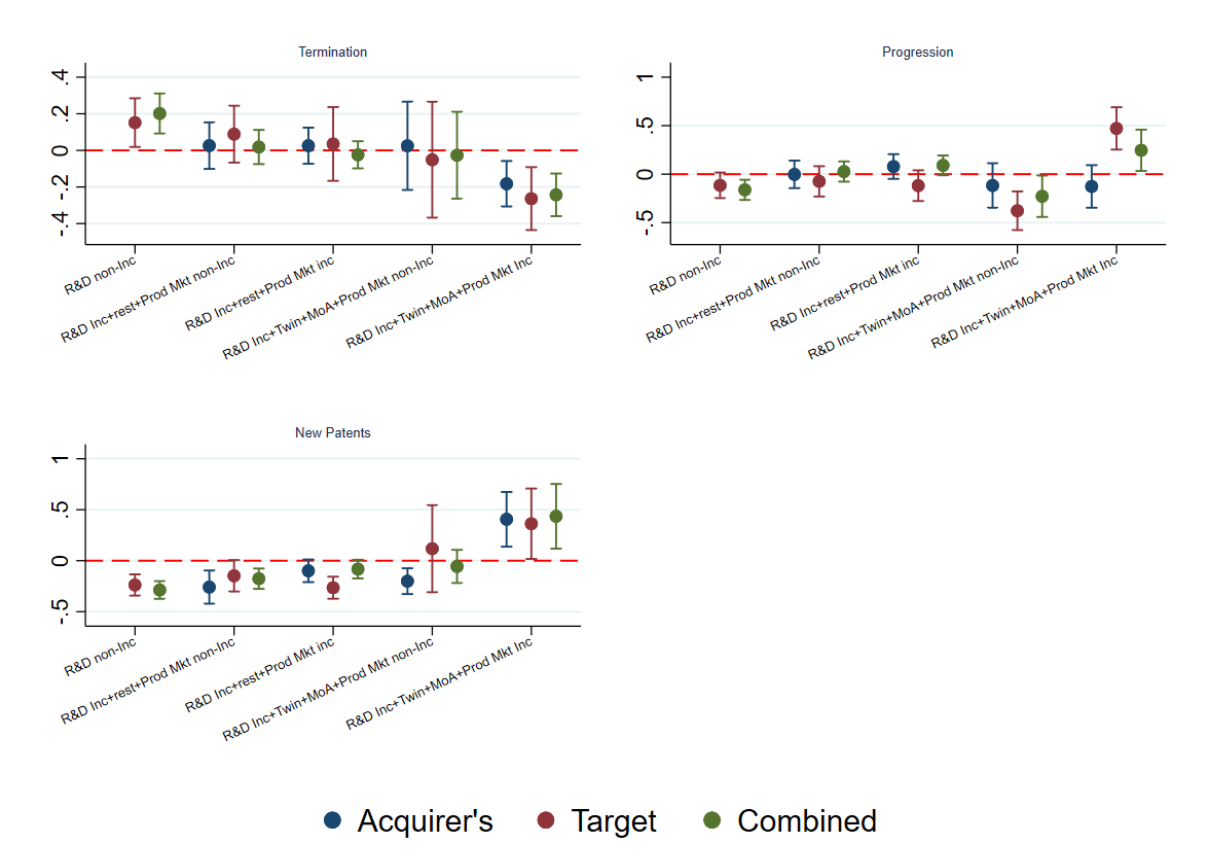
Note: This figure visualizes the estimated effects of M&As depending on the combination of technological closeness, MoA overlap, and market incumbency compared to the exactly matched group of never treated counterfactuals. We report robust standard errors. Full regression results are presented in table D9.

Fig. G3: Robustness - Effects of M&As - Clustering at the firm level



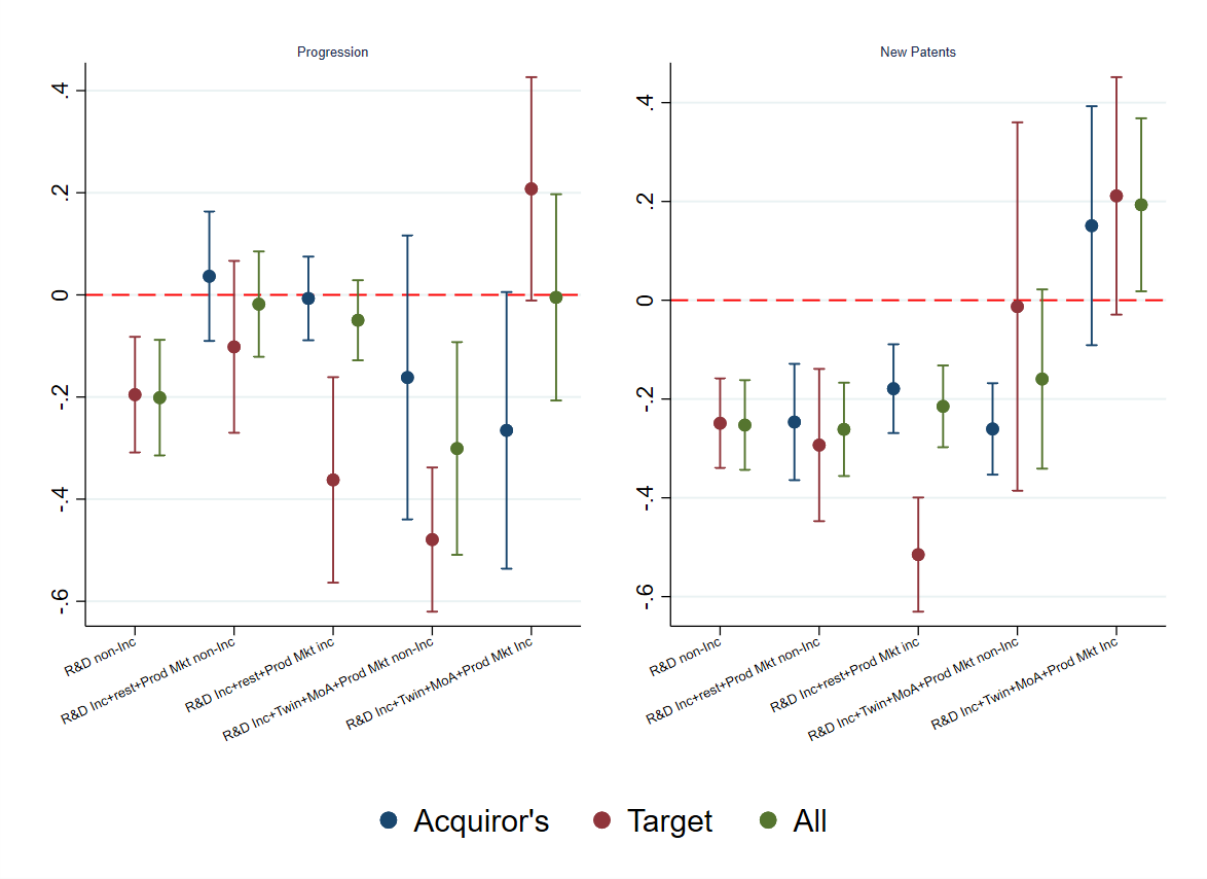
Note: This figure visualizes the estimated effects of M&As depending on the combination of technological closeness, MoA overlap, and market incumbency compared to all never treated projects (no matching). Errors are assumed to be clustered at the firm level. Full regression results are presented in table D10.

Fig. G4: Robustness - Effects of M&As - Clustering at the transaction level



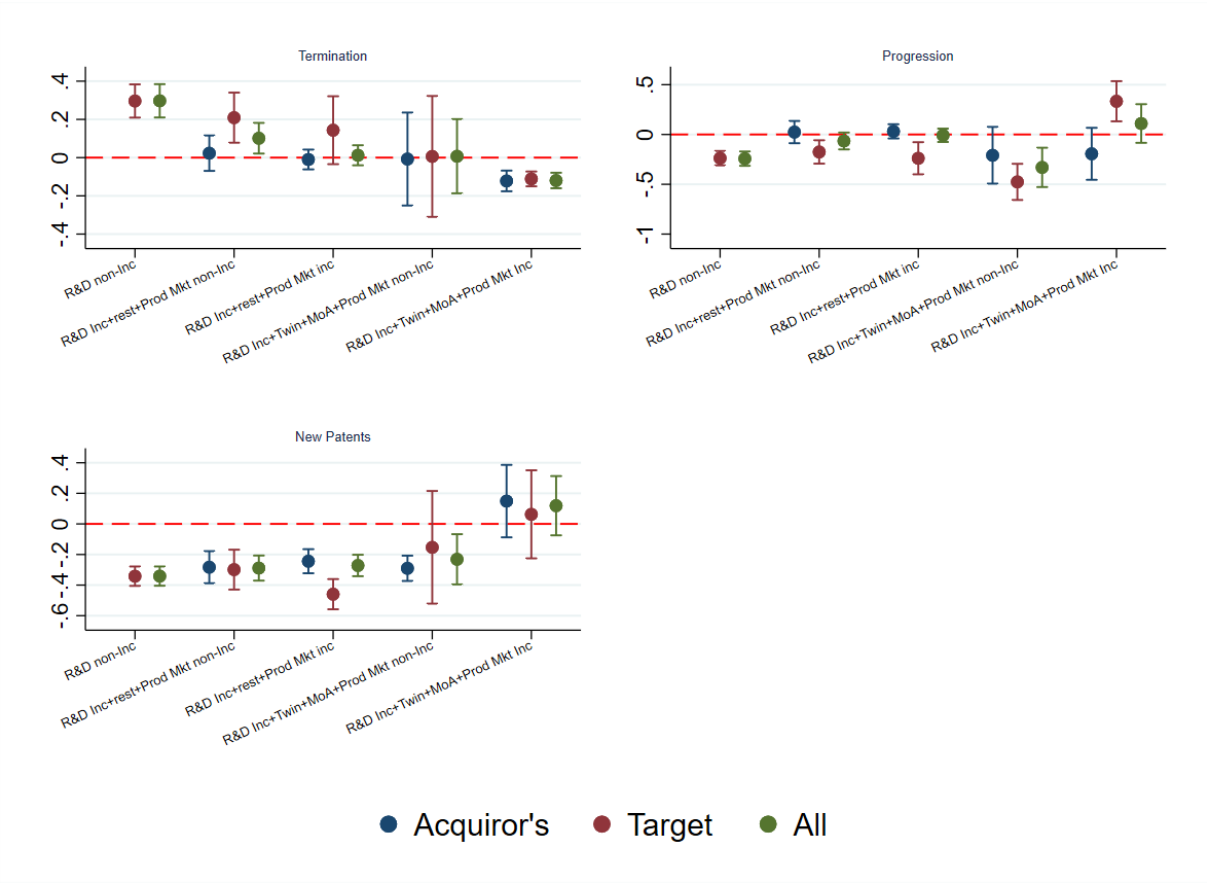
Note: This figure visualizes the estimated effects of M&A depending on the combination of technological closeness, MoA overlap, and market incumbency compared to the pooled group of never treated counterfactuals. Errors are assumed to be clustered at the transaction level. Full regression results are presented in table D11.

Fig. G5: Robustness - Effects of M&As for non-terminated projects



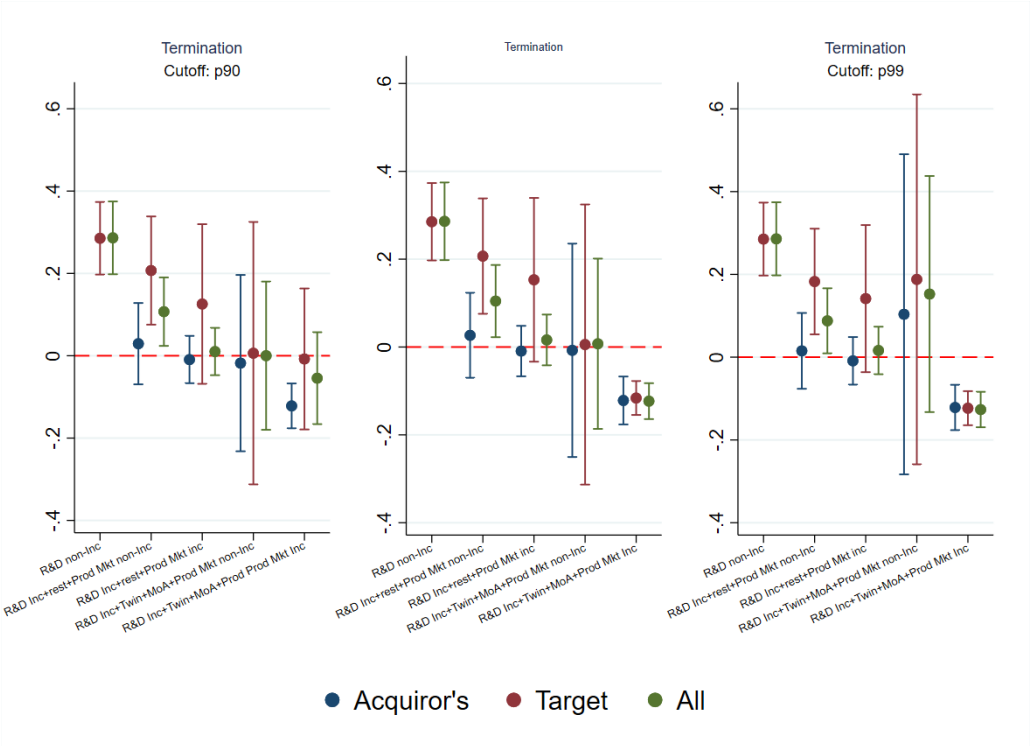
Note: This figure visualizes the estimated effects of M&As depending on the combination of technological closeness, MoA overlap, and market incumbency compared to all never treated projects (no matching). Errors are assumed to be robust. Full regression results are presented in table D12.

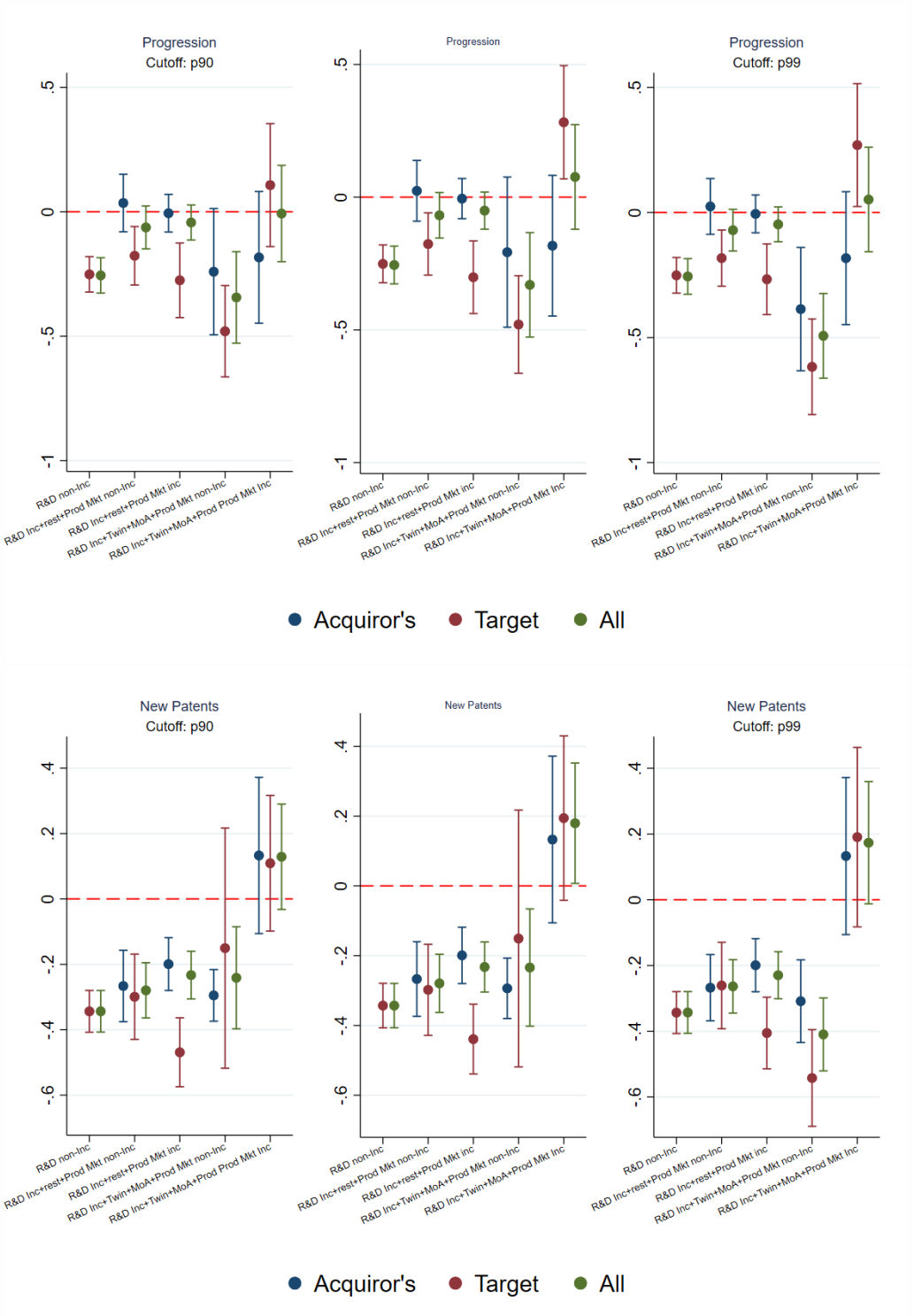
Fig. G6: Robustness - Effects of M&As, Phase III projects included



Note: This figure visualizes the estimated effects of M&As depending on the combination of technological closeness, MoA overlap, and market incumbency compared to all never treated projects (no matching). Errors are assumed to be robust. Full regression results are presented in table D13.

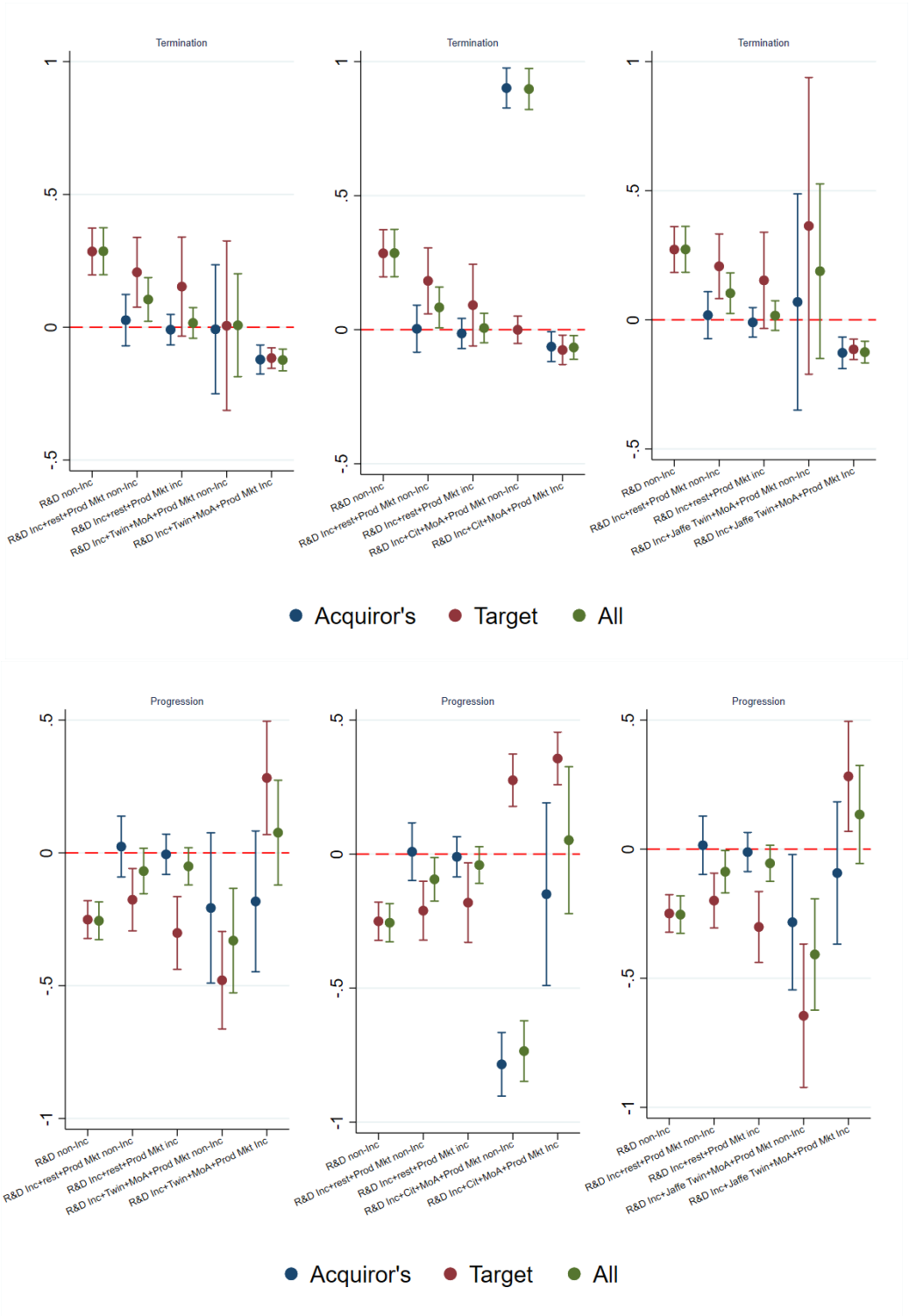
Fig. G7: Robustness - Effects of M&As - Different cutoffs for Twins

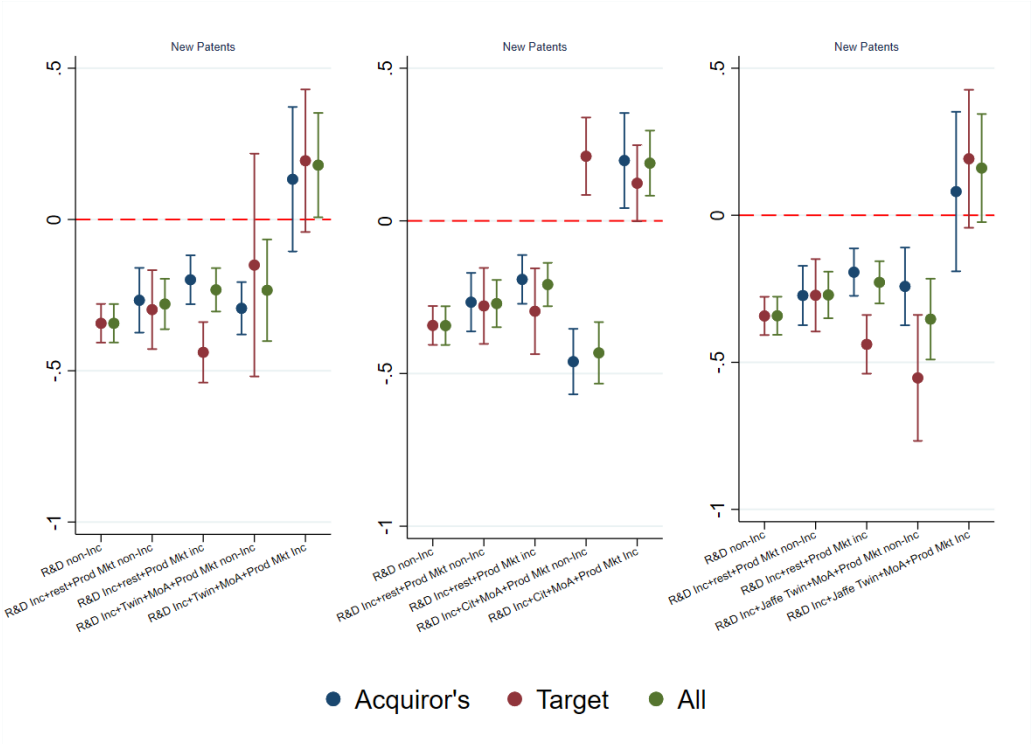




Note: This figure visualizes the estimated effects of M&As on termination, progression, and patenting when varying the cutoff value for the definition of Twin projects, compared to all never treated projects (no matching). Errors are assumed to be robust. Full regression results are presented in tables D18,D7, and D19.

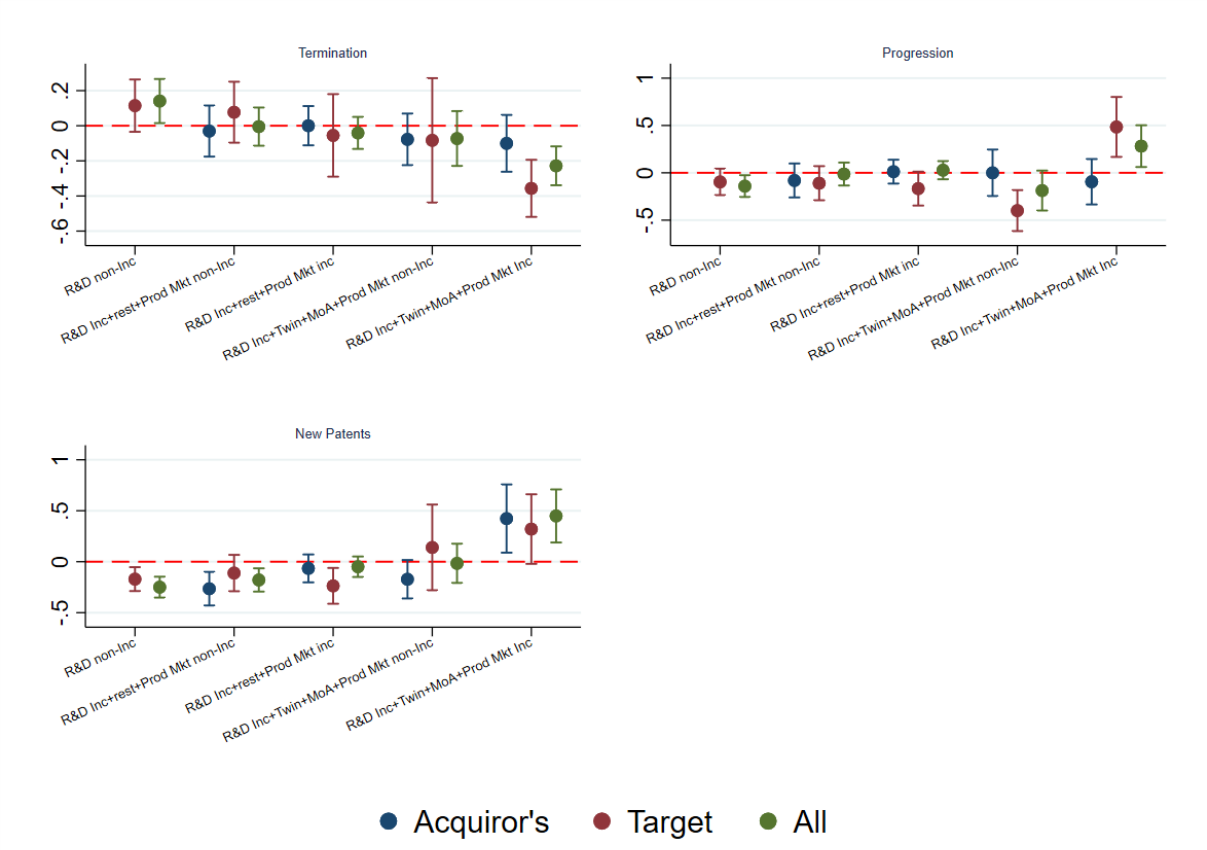
Fig. G8: Robustness - Effects of M&As - Alternative closeness measures





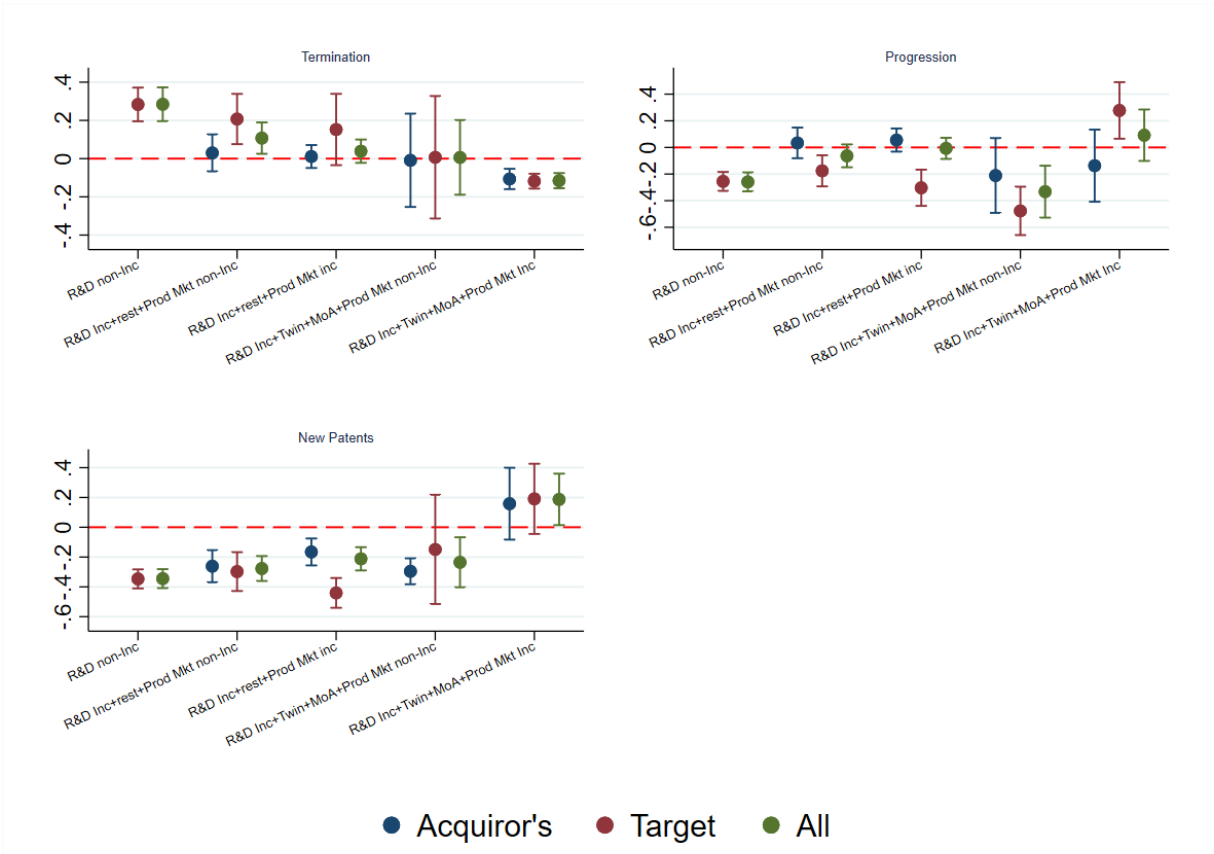
Note: This figure visualizes the estimated effects of M&As on termination rates (top figure), progression rates (middle figure), and patenting (bottom figure), with various measures of technological closeness, compared to all never treated projects (no matching). Errors are assumed to be robust. The first column uses our text-based definition of technological closeness. The second column uses backward patent citations. The third column uses Jaffe's similarity measure based on co-occurrences of IPC patent groups. Full regression results are presented in tables D7,D16, and D17.

Fig. G9: Robustness - Effects of M&As on the sample with core diabetes transactions



Note: This figure visualizes the estimated effects of M&A depending on the combination of technological closeness, MoA overlap, and market incumbency compared to all never treated projects (no matching). The standard errors are assumed to be robust. Full regression results are presented in table D15.

Fig. G10: Robustness - Effects of M&As - Controlling for non-diabetic patents



Note: This figure visualizes the estimated effects of M&A depending on the combination of technological closeness, MoA overlap, and market incumbency compared to all never treated projects (no matching), while controlling for non-diabetic patents. The standard errors are assumed to be robust. Full regression results are presented in table D14.