Growth through Acquisitions

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September 11, 2025

Abstract

Using project-level data from the pharmaceutical industry, I find that acquired projects overlapping with the acquirer's portfolio exhibit a lower likelihood of development. This result is consistent with previous literature and has been interpreted as evidence of anticompetitive behavior. However, I find that this effect is present even if the acquired project overlaps only with the failed projects of the acquirer. Moreover, similar patterns hold for newly initiated projects that overlap with the old projects initiated by the same firm. These findings challenge the prevailing interpretation and suggest the need for alternative explanations, which I propose in this paper.

Keywords: Acquisitions, ownership structure, innovation, R&D.
JEL code: G34, O31, O32.

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1 Introduction

Acquisitions play an important role in the evolution of industries (Baker and Bresnahan, 1985). This is particularly so in the R&D intensive sectors because new ideas are generated by startups which can benefit from synergies by joining industry incumbents. Synergies can come from access to low cost, long term funding and technical expertise related to the practical implementation of the idea and its marketization. Acquisitions also serve as an attractive exit option for venture capital funds because not all projects reach sufficient scale for IPO. However, in a recent study Cunningham, Ederer, and Ma (2021) (CEM henceforth) argue that acquisitions may have negative consequences because large firms can acquire their rivals which are developing potentially competing products and terminate their development to deter future competition. This paper studies the tradeoff between these forces in the context of the pharmaceutical industry.

I use drug development data to analyze the development process of projects after acquisitions. My empirical strategy closely follows CEM and, consistent with the authors, I find that the likelihood of observing a development event decreases after acquisitions. The effect is larger if the acquired drug overlaps with the portfolio of the acquirer in terms of the therapeutic class.[1] CEM interpret the decline of a likelihood of development among overlapping projects as a deliberate intention to deter future competition and label it as killer acquisitions. I present a number of additional empirical results which are hard to reconcile with their interpretation.

In the first part of the analysis, I divide the acquired overlapping projects into two groups. The first group consists of projects that overlap with those in the acquirer's portfolio which, at the time of acquisition, had already been launched as drugs or were under development and later successfully launched. For this set of projects, the rationale proposed by CEM—acquiring rival projects to terminate them—clearly applies. The second group includes acquired projects that overlap with those projects that were in the portfolio of the acquirer at the moment of the acquisition event and were never launched as drugs, in other words, failed projects. I use the term "failed projects," but the outcome may have been unknown at the time of acquisition. For this second group, incentives to deter competition are less likely to apply. Even if we focus on projects that were still under development, it is not clear why, once the acquirer discovered that its own project had failed, it did not reallocate resources to develop the acquired project. At that point, the acquirer should have had the same incentives as the target prior to acquisition. Only under some extreme assumptions acquired projects overlapping with the acquirer's failed projects should exhibit a decline in the likelihood of development. Consequently, any

[1] More precisely the overlap is defined at the therapeutic class and mechanism of action level.

effect should be quantitatively negligible. However, the estimation results reveal that acquired projects overlapping only with the acquirer's failed projects experience a decline in the likelihood of development, and the estimated coefficients are comparable to those for the full sample of overlapping projects. This finding suggests the presence of an alternative mechanism driving the reduced likelihood of development among overlapping acquired projects.

In the second part of the analysis, I follow the logic of overlapping acquisitions and construct an indicator variable for internally overlapping projects. A project initiated by a firm is classified as internally overlapping if, at the time of its initiation, the same firm had earlier initiated another project in the same therapeutic class. Across a broad range of specifications, I find that such overlapping projects have a lower likelihood of development, and the estimated coefficients are comparable to, or even larger than, those estimated for acquired overlapping projects. I further show that this effect persists even when the overlap is only with failed projects, although the estimated coefficient for this specification is somewhat lower. This result cannot be attributed to competition, as the firm itself decides whether to initiate a new project.

Several explanations can account for these results. First, firms accumulate knowledge in a given therapeutic area, which can be valuable when they initiate or acquire a new project in the same domain. This knowledge may provide critical insights during the development process, enabling firms to terminate unpromising projects earlier. One of the key challenges in drug development is that a new drug must not only effectively treat the targeted disease but also avoid harmful side effects. While the development process is designed to identify such effects through multiple stages, certain side effects may appear only within small demographic groups with specific conditions and, therefore, may only be detectable in large samples (Garnier, 2008). A firm with prior experience in a given area may know, for instance, that a particular compound causes a specific type of side effect in patients with a certain genetic profile. Consequently, after acquiring or initiating a new project, the firm may conduct targeted testing and, upon detecting negative outcomes, terminate the project immediately. In contrast, a firm without such knowledge may begin testing in a broader population, where early-stage samples are relatively small and may fail to detect adverse effects, thus proceeding to subsequent stages. Importantly, such experience stems not only from successful projects but also from failed ones. An alternative interpretation could be that large firms which already have a project in a given therapeutic area may seek a superior alternative. As a result, when they initiate or acquire a new project, they apply a higher threshold for continuation.

Under the first explanation, acquisitions create synergies and prevent wasteful investment in unpromising projects. The finding that the decline in the likelihood of a de-

velopment event is observed even among failed projects provides strong support for this mechanism. Under the second explanation, it is possible that the terminated project could have eventually become a drug. However, the motivation for termination in this case differs from a scenario where terminations are driven by deliberate attempts to eliminate competition, with ensuing consequences for welfare and antitrust policy.

Literature Following several high profile acquisitions involving social media technologies, there was an increased interest in the motives and consequences of such deals among regulators, academics and the public. The fact that the companies involved were household names perhaps played a role. Despite the fact that the recent interest in the topic was triggered by developments outside the pharmaceutical sector, this sector has a number of advantages when it comes to econometrically testing various underlying mechanisms. Unsurprisingly, one of the first papers empirically exploring the relationship between mergers and acquisitions and R&D in the economic literature focuses on this sector Ornaghi (2009). First, the sector has a sufficiently long history of high levels of M&A activity (Burns, Nicholson, and Wolkowski, 2012). Second, there are sufficiently detailed datasets reflecting economic outcomes in which economic researchers are interested. This has a lot to do with the fact that the project development process and final products involve human lives. As a result, many activities and products need to follow standard procedures and in many instances the information should be made public. During the development stage, researchers can observe how the projects proceed over time and whether it becomes a final product. Leveraging on this, CEM use the incidence of a development event as a proxy of research effort. There is also abundant information on drugs after the development stage, including prices, sales volumes and advertising expenditures. Several other studies have used this information to study the consequences of M&A on those outcomes (Bonaime and Wang, 2024; Dubois and Majewska, 2022).

The effect of acquisitions on innovation has been studied beyond the pharmaceutical industry as well. Those papers typically use patent data or R&D expenditures, as a measure of innovation (Haucap, Rasch, and Stiebale, 2019; Bena and Li, 2014; Seru, 2014; Phillips and Zhdanov, 2013). The limitations of patents as a measure of innovations have been discussed in the literature (Williams, 2017). Another issue is that after acquisition in most cases it is not possible to observe the activities of the acquired entity separately. For this reason the authors have used patents or R&D expenditures of the combined entity or in the case of Seru (2014) units of the conglomerate. These approaches do not allow to disentangle the underlying mechanism. Moreover, many startups are organized around a specific idea, which may lead to one or several patents, but it is not obvious that all startups can continue patenting at the same pace in the long run. The advantage of the

setting and strategy used by CEM is that the researcher can observe the sequence of steps related to the same project before and after the acquisition.

2 Data

The analysis in this paper is based on the *Pharmaprojects* dataset which is the same dataset used by CEM. I closely follow the authors to construct the final dataset. According to CEM and references therein *Pharmaprojects* includes almost the universe of drugs marketed in the US. In their paper the authors restrict the sample to projects launched until 2010 and track them until 2015. Since I accessed the dataset more recently I extended the sample to projects launched until 2015 inclusive and track them until 2020. One key difference is that I restrict the sample to projects that are currently owned by US firms. For the time period under consideration such drugs account for half of the sample. In the initial stages of this project, I imposed this restriction because of substantial time required to process the data but the data processing revealed several important justifications for this choice. First, the coverage of the acquisition deals between foreign firms in earlier periods is not as good as for the US ones. Second, because the dataset includes drugs marketed in the US, projects owned by foreign firms but not marketed in the US are less likely to be included. This means that when we construct firm-level measures they are more likely to be biased for foreign firms. Third, there are signs that for projects included in the dataset the quality of coverage is better for the US firms (this issue is discussed in more detail in footnote 2). This last point is particularly important and can introduce systematic bias in estimations for questions that are of particular interest. Thus, the focus on the projects owned by the US firms somewhat reduces the sample size, which I partly compensate by extending the study period, but the advantages may outweigh this cost, given that the sample size is already large enough.

The dataset includes a list of drug development projects and events associated with them. Following the authors I classify those events into positive, neutral and negative. The classification is presented in table A1. The exact labeling of events has changed compared with the one presented in the appendix of their paper but it is not difficult to extend the same logic to new labels. For each project-year I construct a development event dummy if there was a positive development in that year. The dataset also reports dates corresponding to each event. Projects enter my analytical dataset starting from the date of the first event. I also use this date as the date of initiation to calculate the project's age, which might not be perfect but it is the best that can be done with this dataset. It is worth emphasizing that an advantage of focusing on US projects is that foreign ones may enter with a delay. For example, a foreign firm may initiate a project and report about

its development based on local regulatory requirements. After some initial positive signs it may take steps aimed at the US or global markets. At that point the project will become more visible for the team of *Pharmaprojects*. Thus, the quality of reporting may be systematically biased for foreign owned projects.[2]

Projects exit the analytical dataset when they are launched or withdrawn. The launch date information is available in a separate column and in the column of events described above as an event "First launch". For some projects which have achieved the highst status launched, the date of launch is not observable but eliminating those drugs does not alter the results of the main specification in CEM, so I keep them in the sample.

In the field company the dataset lists the name of the originator but in the case of projects that were acquired the dataset reports the name of the current owner rather than the true originator. I follow the approach of CEM to recover the name of the true originator. In the field summary which is in a free text format there is a description of the project's development and ownership process. This field contains terms such as "...was under development by Biogen (formerly Convergence Pharmaceuticals)", "Micromet (Amgen) was developing ...", "...Abgenix (now Amgen)...". I select all projects that contain one of the terms: merger, merged, acquired, acquisition, now, formerly, previously. CEM also use a similar approach but they do not include the term "now". I take two additional steps missing in their paper. First, I add cases where the name of company appears in parentheses (like the "Micromet (Amgen)" example above). Second, I add cases in which the name of the company is missing from the summary field. In this case if I find a name of another company which is not listed as a licensee for the same project, then I add it to the list of potential originators. About half of the projects in my sample satisfy one of those conditions. As a result of these steps for each project I create a list of company names. Then, for each project I conduct online searches for each bilateral pair of companies. There are cases when an acquirer itself is acquired. For all cases I find an online article or a regulatory document from which I can identify the relationship between a pair of names. Some pairs involve company name changes without acquisition, which I discard. Based on this information I construct sequences of acquisition events and corresponding dates.

I also use information on the therapeutic class and mechanism of action. Following CEM, I interact therapeutic classes and mechanisms of actions of each project and create

[2]The exploration of the dataset reveals some signs that point in this direction. For example, among projects owned by US firms that entered the dataset before 2015 the likelihood of being launched is 6.4%, for non-US ones the figure is 10.1%. Among launched projects for which we observe at least one activity before the launch, the development phase (the difference between the launch year and the entry into the database) is 6.60 years for the US owned projects and 5.78 for non-US. These observations provide strong signs that foreign projects enter later into the dataset and failed projects are less likely to be covered.

a measure of each drug's "narrow field" and refer to it as TC-MOA. A drug may have multiple TC-MOAs. Then, for each company-year, I construct the set of TC-MOAs where it has a presence. This set is changing over time both because of newly initiated projects by the company itself and because of acquisitions. A given acquired project is considered overlapping if at least one of its TC-MOAs falls into the set of TC-MOAs in which the acquiring company was present the year prior to the acquisition.

CEM exclude all projects that have no positive development during their entire life from the dataset. To be consistent with the authors I do the same. Table A2 provides summary information on the analytical dataset. Although my dataset includes only projects owned by US firms, the difference in terms of the number of projects is not large compared with the one in their paper, 11429 vs 16015. This is partly due to the fact that I slightly extended the study period. The share of acquired projects is 28% (23% in their paper) and overlapping projects 4.8 % (5% in their paper). The fact that there are more acquired projects in my dataset can be driven by more acquisitive growth strategies of US firms, better information availability on deals related to US firms and the additional steps I have taken to identify acquisition as described above.

It is also worthwhile to note that it seems that the data provider has expanded the database retrospectively. For example, in the sample of all countries for projects initiated before 2010 I can observe 39440 projects, while CEM report that their raw dataset has 35712 projects (see footnote 28 of their paper). [3]

3 Empirical analysis

3.1 Empirical specification

My baseline estimating equation is similar to the one presented in CEM with the full set of fixed effects. In particular, I use the following specification:

$$Development_{it} = \beta \cdot I(Overlap)_{it} + \gamma \cdot I(Acquired)_{it} + \alpha_{FE} + \epsilon_{it}, \tag{1}$$

where $Development_{it}$ is an indicator variable taking a value of one if project i experiences a positive development in year t, $I(Acquired)_{it}$ is an indicator if the originator of the

[3] There are some additional issues with the data processing in CEM that are not relevant in the context of my paper but are worth mentioning. In one of the exercises CEM construct a measure of "near expiry" by adding 5 years to the patent filing date. According to the website of the FDA the patent term is for 20 years after the filing, which typically takes place during the development. The five year period after the patent filing can expire even before the drug reaches the market. Additionally, companies enjoy a marketing exclusivity period from 3 to 7 years, depending on the type of drug, starting from the FDA approval date (Lo and Thakor, 2022). So, it is not clear what their "near expiry" measure captures.

project is acquired, $I(Overlap)_{it}$ is an indicator if the project overlaps with the portfolio of the acquirer. I follow CEM and cluster standard errors at project level. In the baseline specification the authors include project fixed effects and TC-MOA interacted with age fixed effects. The latter require some discussion. As was mentioned earlier, a given project may have multiple TC-MOA, which the authors also mention in their paper. According to the replication code, the authors use *reghdfe* command in *Stata*, which requires a unique TC-MOA for each project. This detail is not discussed in their paper and it is not clear how they have selected the fixed effect.[4] In this situation I consider two alternative approaches. The first one selects TC-MOAs which are the most frequent in the dataset. The other extreme is to select TC-MOAs that are least frequent. Some TC-MOAs are unique, as a result by selecting the least frequent ones many observations get absorbed by fixed effects and do not contribute to the identification. This problem is less severe in the case of the first approach and it seems to be a more reasonable choice, so I use that approach throughout the paper and also show the results for the second approach for their baseline specification.

In section 2 I mentioned that an acquirer of a company may be acquired itself. In the case of $I(Acquired)_{it}$ indicator this does not have any implications because the term switches to one and remains the same until the end of the sample. In the case of $I(Overlap)_{it}$ acquisition chains matter. If the project does not overlap with the portfolio of the first acquirer but overlaps with the portfolio of the accuser's acquirer, then the variable switches to one only after the second event. In CEM the overlap term does not have a time subscript, so it is not clear whether they take the same step. However, the number of such cases is not large, so the effect on the estimated coefficients is unlikely to be large under alternative approaches.

3.2 Baseline results

Column 1 in table 1 presents the estimation results of the equation 1 with age and project fixed effects. The acquisition indicator has a highly statistically significant negative effect on the likelihood of a development event. However, according to this specification acquired overlapping projects do not have an additional negative effect on project development. This specification differs from the baseline specification of CEM because age fixed effects are not interacted with TC-MOA. Nevertheless, it is interesting to run it because age-TC-MOA fixed effects are very demanding and as a result of their inclusion a substantial fraction of observations get absorbed. This specification is also similar to

[4]Since the paper uses a commercial dataset, the replication files do not include the underlying data and *Stata* codes are available only partially. Some steps in the data cleaning are missing and it is not possible to infer how the authors have dealt with multiple TC-MOA.

Table 1: Acquisitions and project development

	(1)	(2)	(3)	(4)	(5)
$I(Acquired)_{it}$	-0.043***	-0.032***	-0.022***	-0.399***	-0.298***
	(0.004)	(0.006)	(0.006)	(0.052)	(0.068)
$I(Overlap)_{it}$	-0.005	-0.014	-0.021**	-0.464***	-0.364***
	(0.008)	(0.010)	(0.010)	(0.142)	(0.138)
R-Adj./Pseudo R	0.217	0.214	0.200	0.209	0.214
N	169774	110096	85783	169752	110096
Fixed effects					
Age	Yes	No	No	No	No
Age-TC-MOA	No	Yes	No	Yes	Yes
Age-TC-MOA^{min}	No	No	Yes	No	No
Project	Yes	Yes	Yes	Yes	Yes
Estimation method	OLS	OLS	OLS	PPML	PPML

Notes: The dependent variable is an indicator for a development event. $I(Acquired)_{it}$ is an indicator switching to one starting from the acquisition year. $I(Overlap)_{it}$ is an indicator variable if the acquired project's TC-MOA overlaps with one of the projects in the acquirer's portfolio. In constructing Age-TC-MOA fixed effects for projects with multiple TC-MOA the one with maximum frequency in the database is selected and for Age-TC-MOA^{min} the TC-MOA with minimum frequency is selected. * (**) (***) indicates significance at the 10 (5) (1) percent level. Standard errors are clustered at project level.

the classical two-way fixed effects estimation with the difference that year fixed effect is replaced with age fixed effect. Replacing age with year does not change the picture.

The second column includes the interaction of age with TC-MOA fixed effects. In this column, for projects with multiple TC-MOAs I select the ones that are most frequent in the database. As can be seen the number of observations goes down substantially because *Stata* excludes singleton observations.[5] In this specification the coefficient on the overlap dummy gets larger in absolute size but it is still not statistically significant at the conventional levels. The third column uses the least frequent TC-MOA for projects with multiple TC-MOAs to construct the fixed effects. Naturally, in this case the number of observations actually used in the regression drops further. Importantly, for this specification the size of the coefficient and its statistical significance increases to 5% which is the same as in CEM. It is also worthwhile to note that my estimated coefficient is still smaller than the one in CEM but in terms of percent changes the results are closer because in my sample the unconditional likelihood of a development event is 15%. CEM report that in their dataset it is 19.9%.[6] These differences are primarily driven by the factors described in sec-

[5]Note that CEM report only the total number of observations not the number of observations actually used. The total number of observations in column 2 is 169933.

[6]More specifically, the estimates in column 4 of table 2 of their paper imply that being acquired by a firm

tion 2. Specifically, foreign projects enter the dataset selectively and have higher success probabilities. Ex post successful projects have much higher likelihood of experiencing a development event in a given year. Thus, the inclusion of foreign projects artificially increases the unconditional likelihood of development events. The fact that I am using a longer time period also contributes to these differences because unsuccessful projects remain in the dataset.

From this analysis we can note that age-TC-MOA fixed effects play an important role. The particular way of selecting fixed effects also matters. It seems that the first criteria of selection is more reasonable because it increases the sample contributing to the identification. One may come up with an argument to justify the usage of the least frequent TC-MOAs. However, when I restrict the estimation sample to the observations used in column 3 and run the regression with the most frequent TC-MOA fixed effects (column 2), the estimated coefficient on the overlap indicator moves in the direction of column 3, which suggests that at least partly the result is driven by imposing an unjustified restriction on the sample.

An important issue with estimating the specification 1 is that the outcome variable is an indicator which takes values of 0 and 1. In such contexts OLS is not be the most preferred estimator. At the same time, Probit regressions are not feasible, given the number of fixed effects. Given the number of unique projects it is not even possible to run a Probit specification with project fixed effects, let alone age-TC-MOA fixed effects. An alternative that can be considered is the Poisson Pseudo Maximum Likelihood (PPML) approach which allows the inclusion of large number of fixed effects. In columns 4 and 5 I present the results for PPML specifications both without age-TC-MOA fixed effects and with.[7] For those specification we observe consistently highly statistically significant negative coefficients for the overlap indicator in both specifications.

3.3 Heterogeneity among overlaps

To better understand the mechanism behind the negative coefficient on the overlap indicator variable, in this subsection I split the portfolio of the acquirer into two groups and define overlap with respect to those groups. The fist group includes the projects that are in the portfolio of the acquirer in year t and eventually were launched. This includes

with an overlapping project is associated with a 23.4% $(0.041/(0.199-0.024))$ lower development probability than otherwise similar drugs that are acquired by a non-overlapping acquirer. The corresponding figure based on my estimates in column 3 of table 1 is 16.4% $(0.021/(0.15-0.22))$, which is lower but the differences are not too large.

[7]For PPML estimation with fixed effects the estimator drops not only singleton observations but also observations that are fully separated by the fixed effects. As a result the number of observations are smaller compared with the corresponding columns estimated with OLS.

both projects that were launched before year t and those that were under development in year t and ex post succeeded.[8] The second group is the complement of the first one and includes the projects that were in the portfolio of the acquirer in year t and were not launched by 2025. This set includes both projects that were already failed at the moment of acquisition and those that were still under development. Note that the estimations include only projects that were initiated before 2015, so those projects that were initiated by the acquirer and still were under progress at the moment of the acquisition had sufficient time for development, so the fraction of still active projects is negligible. For both groups I construct a firm-year set of TC-MOAs and define $I(Overlap^L)_{it}$ and $I(Overlap^F)_{it}$ variables for launched and failed projects, respectively. In very rare cases these sets can intersect. For example, a firm may have a launched and a failed project that have the same TC-MOA. For those cases I exclude the respective TC-MOA from the set of failed projects. This step has a negligible effect on the results presented below but must be taken to make sure that the results for failed projects are not contaminated by such intersections.

The results of estimations for both types of overlaps are presented in table 2. For each type I show the linear specification with age-TC-MOA fixed effects and two PPML specification that include non-interacted and interacted fixed effects.[9]. The first three columns show the results for launched projects. We can observe that $I(Overlap^L)_{it}$ coefficient has a negative sign in all cases but its statistical significance is relatively low. The following three columns show the results for failed projects. For this set we also observe negative coefficients and for the PPML specifications the estimated coefficients turn out to have rather high levels of statistical significance. There are 138 target projects overlapping with launched ones and 427 overlapping with failed ones. These differences can explain why estimated coefficients for the $I(Overlap^F)_{it}$ variable are more precise.[10]

This result is hard to reconcile with the killer acquisition hypothesis. As I mentioned above, this set includes projects that were already failed at the moment of acquisition and those that were under development but failed later. For the first subset the acquired target poses no threat because those projects have already failed. For the second subset there might be some competition threat, which I discuss in more detail.[11] A large firm can have

[8] I do not split the launched projects further based on these two types because in total there are 138 such overlaps, which is not a large number.

[9] For the linear specification I do not display the results without interacted fixed effects because the indicator on the overlap variable is never significant even in the full specification (see table 1 column 1)

[10] Note that the total number of overlapping projects in table A2 (551) is slightly lower than the sum of 138 and 427. This is due to the fact that there could be chains of acquisitions. In such cases an acquired project may overlap with failed projects of the first acquirer and a launched projects of the second acquirer. Given the small number of those cases excluding them does not alter the results.

[11] I do not split the sample of failed overlapping projects into two groups for three reasons. First, in the dataset there is no strict definition of a termination date. Second, splitting the sample decreases the number of treatments and decreases the statistical significance of the estimated coefficients. Third, for the

Table 2: Launched and failed overlaps

	(1)	(2)	(3)	(4)	(5)	(6)
$I(Acquired)_{it}$	-0.034***	-0.455***	-0.366***	-0.034***	-0.403***	-0.323***
	(0.005)	(0.051)	(0.060)	(0.006)	(0.052)	(0.067)
$I(Overlap^L)_{it}$	-0.022	-0.059	-0.299			
	(0.023)	(0.263)	(0.272)			
$I(Overlap^F)_{it}$				-0.010	-0.541***	-0.326**
				(0.010)	(0.157)	(0.149)
R-Adj./Pseudo R	0.214	0.209	0.195	0.214	0.209	0.195
N	110096	169752	62327	110096	169752	62327
Fixed effects						
Age	No	Yes	No	No	Yes	No
Age-TC-MOA	Yes	No	Yes	Yes	No	Yes
Project	Yes	Yes	Yes	Yes	Yes	Yes
Estimation method	OLS	PPML	PPML	OLS	PPML	PPML

Notes: The dependent variable is an indicator for a development event. $I(Acquired)_{it}$ is an indicator switching to one starting from the acquisition year. $I(Overlap^L)_{it}$ is an indicator variable if the acquired project's TC-MOA overlaps with one of the launched projects in the acquirer's portfolio, including the ones that were under development at the moment of the acquisition. For $I(Overlap^F)_{it}$ overlaps are defined at the level of failed projects, i.e., those that were never launched. In constructing Age-TC-MOA fixed effects for projects with multiple TC-MOA the one with maximum frequency in the database is selected. * (**) (***) indicates significance at the 10 (5) (1) percent level. Standard errors are clustered at project level.

an incentive to acquire a smaller rival even when both projects are under development with unknown outcomes. The rationale is that if the large firm's project succeeds and the small firm is not acquired and that project also succeeds, then the large firm will face an undesirable competition. It is not clear though, why the acquirer should develop its own project and not the other one, since both are at the development stage. If the chances of success of the target project are low or it is of lower quality, then perhaps it is not even worth spending time and money on that deal since the expected effect from competition is low. Nevertheless, if the acquisition takes place and over time the acquirer finds out that its own project failed, then it should revive the acquired overlapping project. One may argue that reviving projects is associated with some costs. If that is the case, then the acquirer can keep the target project running at a minimal scale as an insurance option. In practice it does not seem that restarting a development is associated with huge costs because the development event labeled "Development Restarted" is very frequent in the dataset.

This discussion above implies that there is only a tiny chance that acquired projects which overlap with the failed ones should experience a decline in the likelihood of development. That in turn implies that the estimated coefficient on $I(Overlap^F)_{it}$ should be zero or much smaller in magnitude compared with the full sample of overlapping projects. However, the estimated coefficients for targets overlapping with failed projects are close or larger than the equivalent ones for the full sample or the sample of targets overlapping with launched projects.[12]

One plausible explanation that can be consistent with the results in Table 2 is that the negative coefficient on the likelihood of development of the overlapping acquired projects is because the acquirer has more experience with project in that area and engages in more targeted testing to identify side effects and upon finding them terminates the project. In the following section I provide further evidence corroborating this interpretation.

3.4 Overlaps within the firm

In this subsection I explore the dynamics of the development of projects which are initiated by a given firm and overlap with the existing portfolio of the same firm. To that end,

fists subset there is absolutely no competition threat. For the second subset there is a weak competition threat. This means that even if we assume that all projects were under development we should observe much weaker effects compared with all overlapping projects, which turns out not to be the case.

[12] I have also explored the reverse effect of overlapping acquisitions on the projects that were in the portfolio of the acquirer. More specifically, I have estimated a dynamic specification, similar to 1, where the sample is restricted to non-acquired projects and the treatment dummy takes a value of one after the year the initiator of a given project acquires a target that overlaps with the focal project. I did not find any statistically significant reverse effects on own projects.

Table 3: Own initiated overlaps

	(1)	(2)	(3)	(4)	(5)
$I(Own\ overlap)_i$	-0.020***	-0.017***	-0.021***		-0.018***
	(0.003)	(0.004)	(0.005)		(0.005)
$I(Own\ overlap^F)_i$				-0.014***	
				(0.005)	
$log(Project\ order_i)$					-0.011***
					(0.004)
R-Adj.	0.135	0.179	0.176	0.176	0.178
N	169895	110176	70617	70617	70492
Fixed effects					
Age-TC-MOA	No	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes
Year	No	No	No	No	Yes
Sample criteria					
Non-acquired only	No	No	Yes	Yes	Yes

Notes: The dependent variable is an indicator for a development event. $I(Own\ overlap)_{it}$ is an indicator variable if the newly initiated project's TC-MOA overlaps with one of the existing projects in the company's portfolio. For $I(Overlap^F)_{it}$ overlaps are defined at the level of failed projects, i.e., those that were never launched. $Project\ order_i$ is the order of the project in the portfolio of a given company sorted by the initiation year. * (**) (***) indicates significance at the 10 (5) (1) percent level. Standard errors are clustered at project level.

I introduce a new variable $I(Own\ overlap)_i$ which takes a value of one for newly initiated projects which overlap with one of the projects in the portfolio of the same firm initiating the focal project. For this specification I cannot include project fixed effects because the treatment is not changing over time within a project. At the moment of the initiation, the project either overlaps or not and it does not change over its lifetime. Instead, I include company fixed effects. The results of estimations presented in table 3 show that projects initiated by a firm that overlap with its current portfolio are less likely to experience a development event. This result is very robust and survives across different specifications. In column 3 I exclude the projects that are ever acquired which increases the estimated size of the coefficient. This specification seems more responsible because it compares only projects initiated by the same firm. Importantly, the estimated coefficients are similar or even larger compared with the equivalent ones for acquired overlapping projects reported in column 2 of table 1. Since the results are robust and highly statistically significant, I present the estimates only for the OLS specifications and provide the PPML estimates in appendix A3.

There could be alternative interpretations for this result other than knowledge obtained from experience, which was mentioned in the previous subsection. For example,

one may argue that firms with projects in a given TC-MOA have a higher continuation threshold, so if they see a less promising project than their existing drug, they terminate it. A related story is that firms may launch multiple projects sequentially and then along the progression make a decision and pick the best one. These are plausible explanations but they have completely different welfare and antitrust implications compared with the killer acquisition interpretation. Nevertheless, I can take some steps to assess the relative importance of the experience effect versus those alternative channels. In order to do so, I define $I(Own\ overlap^F)_i$ variable which takes a value of one if a given initiated project overlaps with the existing projects that were never launched. This variable follows the same logic as the one presented in the previous subsection. If the coefficient on the $I(Own\ overlap^F)_i$ term is negative, then I can claim that knowledge plays a role because if the project of interest was internally competing with other projects which never became a drug the firm has no incentives to exert less effort on this project, if anything it should exert more. The results of the estimation are presented in column 4 and show a robust negative effect. The coefficient is somewhat smaller in magnitude, compared with the full portfolio, which suggests that the alternative explanations listed in this paragraph (not killer acquisitions) play a role. However, there is an additional quantitatively large effect that can be attributed to knowledge obtained from past experience.

In the last column I add another control variable which is the order of the project in the portfolio of a firm based on the date of the initiation. The idea is to explore whether the experience of a firm reduced the likelihood of a development event within own initiated projects even outside its own TC-MOA. In this specification I also include year fixed effects because over time firm experience is increasing but at the same time regulatory requirements have became stricter which affects the development process (Burns et al., 2012).[13] The results reported in the last column show that the experience of a firm reduces the likelihood of development events in the subsequent projects. The role of experience is particularly strong within TC-MOA but there is also a general effect that reduces the likelihood of development events across all projects. This result can partly explain why acquisition in general reduce the likelihood of development events for non-overlapping drugs. CEM do not provide a thorough explanation why non-overlapping acquisitions decrease drug development. I discuss this issue in more detail in appendix B.

[13]Since this specification directly explores the role of experience, the inclusion of year fixed effects is required because experience is correlated with time. In general it makes sense to include such fixed effects in all specifications. To be consistent with CEM I report the results with the same set of fixed effects as the baseline specification in their paper but adding year fixed effects does not noticeably alter the results reported in this paper. The estimated coefficient on experience in column 5 of table 3 drops but still remains significant at 5 % level in a specification without year fixed effects.

4 Conclusions

The empirical findings documented in this paper cast doubt on the view that large pharmaceutical firms acquire young biotech companies developing competing drugs with the aim of reducing competition. A more plausible explanation is that large firms possess greater expertise in certain therapeutic areas, which enables them to make better-informed decisions throughout the development process. This leads to earlier termination of unpromising projects. Given that small biotech firms are more likely to initiate novel discoveries (Burns et al., 2012), the opportunity to be acquired by a pharmaceutical company with deep expertise in the relevant area can create synergies and reduce wasteful research efforts.

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Appendix

A Additional tables

Table A1: Measuring drug development

Event	Development event?
Change in Licensee Status	-
Chemical Structure Reported	Yes
Development Restarted	Yes
Development Suspended	No
Discontinuation Confirmed	No
Disease Phase Change	Yes
Drug Added	-
Emergency Use Authorization Granted	Yes
Expedited Review Designation Granted	Yes
Filing Withdrawn	No
First Approval	Yes
First Filing	Yes
First Launch	Yes
Global Status Advance	Yes
Global Status Reversion	-
IND Filing	Yes
Lead Identified	Yes
License Discontinued	-
New Approval	Yes
New Disease	Yes
New Filing	Yes
New Launch	Yes
New Licensee	-
New Licensing Opportunity	-
New Mechanism	Yes
New Patent	Yes
New Target	Yes
New Therapeutic Class	Yes
No Development Reported	-
Nonproprietary Name Granted	Yes
Novel Target Identified	Yes
Orphan Drug Status Granted	Yes
Regulatory Warning	-
Supplemental Approval	Yes
Supplemental Filing	Yes
Withdrawn from Market	No

Notes: This table shows the list of development events in *Pharmaprojects* and their classification following the logic in Cunningham et al. (2021).

Table A2: Project summary

	Total	Acquired	Overlapping acquired
Projects	11429	3195	551

Table A3: Own initiated overlaps: PPML

	(1)	(2)	(3)	(4)	(5)
$I(Own\ overlap)_i$	-0.137***	-0.123***	-0.134***		-0.104***
	(0.024)	(0.024)	(0.028)		(0.029)
$I(Own\ overlap^F)_i$				-0.093***	
				(0.030)	
$log(Project\ order_i)$					-0.044***
					(0.016)
Pseudo R	0.133	0.147	0.143	0.143	0.143
N	169416	62365	39822	39822	39744
Fixed effects					
Age-TC-MOA	No	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes
Year	No	No	No	No	Yes
Sample criteria					
Non-acquired only	No	No	Yes	Yes	Yes

Notes: The dependent variable is an indicator for a development event. $I(Own\ overlap)_{it}$ is an indicator variable if the newly initiated project's TC-MOA overlaps with one of the existing projects in the company's portfolio. For $I(Overlap^F)_{it}$ overlaps are defined at the level of failed projects, i.e., those that were never launched.. $Project\ order_i$ is the order of the project in the portfolio of a given company sorted by the initiation year. * (**) (***) indicates significance at the 10 (5) (1) percent level. Standard errors are clustered at project level.

B The general effect of acquisitions

Across all specifications we observed that the main acquisition variable $I(Acquired)_{it}$ had a negative coefficient with a very high level of statistical significance, which deserves an interpretation. CEM suggest that this could be because TC-MOA is a very narrow definition of overlap and run a specification that defines overlap more broadly at TC level ($I(Overlap^{TC})_{it}$). In the first column of table B1 I replicate their result with this additional term (reported in table F1 of their paper) and find that the acquisition term decreases only slightly compared with corresponding specifications in columns 2 of table 1 but we still observe a robust negative effect.

Table B1: The general effect of acquisitions

	(1)	(2)
$I(Acquired)_{it}$	-0.027***	-0.026*
	(0.008)	(0.015)
$I(Overlap)_{it}$	-0.008	0.005
	(0.012)	(0.012)
$I(Overlap^{TC})_{it}$	-0.012	
	(0.010)	
R-Adj./Pseudo R	0.214	0.201
N	110096	110063
Fixed effects		
Age-TC-MOA	Yes	Yes
Project	Yes	Yes
Firm	No	Yes
Estimation method	OLS	OLS

Notes: The dependent variable is an indicator for a development event. $I(Acquired)_{it}$ is an indicator switching to one starting from the acquisition year. $I(Overlap)_{it}$ is an indicator variable if the acquired project's TC-MOA overlaps with one of the projects in the acquirer's portfolio. For $I(Overlap^{TC})_{it}$ overlaps are defined at the level of therapeutic classes. * (**) (***) indicates significance at the 10 (5) (1) percent level. Standard errors are clustered at project level.

One possibility is that acquiring firms have different development patterns in general. This can be because those firms are more experienced. The results in the last column of table 3 lend some support to this point. It also could be that large firms have different reporting patterns, which can drive down the coefficient on the $I(Acquired)_{it}$ indicator. To explore this point, I introduce firm fixed effects which can change over time as a result of acquisitions. The results of the OLS specification are presented in the second column.

The estimated coefficient on acquisition variable is almost twice smaller compared with the specification without firm fixed effect (column 2 of table 1) and statistically significant only at 10% level. For PPML specifications with company fixed effects the estimated coefficients on $I(Acquired)_{it}$ are close to 0 and statistically not significant. However, the software (*Stata*) produces a working and for that reason I do not report the results.[14]

In addition to the learning and experience channel discussed so far, there is one more phenomenon that deserves to be mentioned, in particular when it comes to the general effect of acquisitions. There is some evidence, based on both academic studies and business news, that the incentives of the managers and shareholders are not aligned and the managers have asymmetrically higher private benefits if the project succeeds. Thus, managers can push forward projects with negative net present value. Guedj and Scharfstein (2004) provide evidence for these kinds of behavior using data from the pharmaceutical industry. The authors show that the problem is particularly acute in small firms with cash reserves, meanwhile large firms benefit from internal capital markets (Stein, 1997; Shin and Stulz, 1998) and abandon unpromising projects. In the framework proposed by Stein (1997) the manager of the single-project firm is reluctant to return funds to shareholders even if the project turns out to be poor because the manager loses the private benefits from running the project. In the case of the large firm this is less of a problem because the manager has multiple projects and by terminating one of the projects he/she still can get the private benefits by running the other projects. Another interesting piece of evidence in support of this phenomena comes from a recent initiative to launch a fund which aims to acquire listed biotech firms and return cash to shareholders (Kuchler, 2025). This initiative is expected to be profitable because many listed biotech firms trade below their book value. In the news article a biotech expert is quoted saying that, "Management teams have frequently been happy to hang on and try different approaches because they still have cash raised in the boom times." The presence of such frictions can play a role in explaining why projects experience a decline in development events after acquisition even when they do not overlap with the acquirer's portfolio.

[14]The specific issue is "ReLU separation check: maximum number of iterations reached."