Competition and Innovation Revisited: A Project-Level View

Jon A. Garfinkel

Tippie College of Business, University of Iowa, United States

Mosab Hammoudeh

Henry Bernstein College of Business Administration, University of New Orleans, United States

Forthcoming in the Review of Financial Studies

Abstract

We offer new evidence on the relationship between competition and innovation that overcomes two measurement difficulties compromising the extant literature: aggregation at either firm level (or higher) of innovative activity, and the mediating influence of distance-to-technological-frontier. FDA awards of Breakthrough Therapy Designations (BTDs) on specific drugs, instrument stochastic unleveling of therapeutic (i.e., product) markets. Rivals' innovative responses generally show an inverted-U pattern in ex ante competitiveness of the shocked market. However, the shape of the relation changes with distance to technological frontier in that market, proxied by whether the rival project uses one of the technologies embedded in the BTD-awarded drug. (*JEL* L65, D25, O31, O32, D4)

We thank two anonymous referees and especially editor Lauren Cohen for both insightful comments and suggestions as well as encouragement. We are very grateful to both Dennis Erb and Richard Peter for their consistent feedback as well as (numerous) patient explanations. Thanks also go to Manuel Adelino, Matt Billett, Nick Bloom, Tony Cookson, Cameron Ellis, Michael Ewens, Manuel Hermosilla, Jerry Hoberg, Jennifer Kao, Josh Krieger, Xuelin Li, Katie Miller, Gordon Phillips, N. Prabhala, Giorgo Sertsios, and Richard Thakor and seminar participants at Johns Hopkins University and the U.S. FDA for helpful comments and suggestions. We thank Brandon Boyd, Ketan Patel and Max Penverne at Cortellis (Clarivate) for data provision and guidance and Zaid Assaf for research assistance in assigning drugs to ICD-10 codes. We also thank Manuel Hermosilla for providing policy exposure measures on drugs and Jerry Hoberg for data on firm scope. All errors are the responsibility of the authors. This paper previously circulated under the title "Competition Threats and Rival Innovation Responses: Evidence from Breakthrough Therapies." Send correspondence to Jon A. Garfinkel, jon-garfinkel@uiowa.edu.

The relationship between competition and innovation is of crucial interest to academics, regulators, firms, and consumers. It influences corporate behavior, guides policymaking, and has broad economic and societal influence. Yet the shape of that relationship remains inconclusive with oft-conflicting empirical results.[1] We submit that measurement difficulties compromise consensus, especially as theory offers varying frameworks to guide empirical work.[2] We summarize evidence of two measurement challenges in the literature on the competition-innovation relationship, and then provide original results highlighting one of them in a standard setting. We offer brand new tests in a near-ideal setting—the pharmaceutical industry—designed to overcome the two measurement difficulties. Our research supports both the workhorse model of Aghion et al. (2005) and an extension that recognizes greater variability in technological prowess of firms facing sudden changes in their competitive position.

The two common measurement problems we address are aggregation of innovation proxies, and distance to technological frontier estimation. In the former, the vast majority of empirical research linking competition with innovation is run at the firm level or higher. As long as the observation level contains potential variation in innovative activity underneath a single "hood," for example, when a firm operates in multiple product markets that it could innovate in each of, then the observation-level response measure is aggregated. In the latter, few papers have attempted to estimate a corporate responder's distance to the product market's technological frontier, and those that have often rely on data that conflate technological supremacy with pricing information (De Loecker and Goldberg 2014).

Table 1 summarizes the basics of these difficulties (see Section 1.1 for details). Across three very different periods of research on the competition-innovation relationship, we see three recurrent themes. First, the concluded shape of the empirical relation varies. Second, there is potentially high-level

[1] A few examples include Hombert and Matray (2018), Hoberg, Li, and Phillips (2021), and Autor et al. (2020), all of whom document negative relationships between competition and innovation, whereas Phillips and Zhdanov (2012) and Bloom, Draca, and Van Reenen (2016) document positive relationships.

[2] For the negative relationship, see Schumpeter (1943), Salop (1977), Dixit and Stiglitz (1977), Romer (1990), Aghion and Howitt (1992), and Grossman and Helpman (1991). The contrasting view of a positive relationship is presented in Hart (1983) via agency considerations, and by Aghion et al. (2001) with step-by-step innovations. Aghion et al. (2005) derive an inverted-U relationship. More recent work relaxes constraints on innovation (in the form of distance to technological frontier; see especially Hashmi 2013).

aggregation in the measurement of the relationship, with cross-country and/or within-country cross-industry (or -market) sampling. Third, a minority of the papers attempt to measure distance-to-frontier.

Given selection concerns with a small set of empirical papers, we buttress with our own empirical analysis of the relationship between competition and innovation in a standard setting. We then ascertain whether aggregation problems might have influenced the results.[3] Specifically, we study U.S. manufacturing firms' innovation responses to Chinese import competition, and how it is influenced by potential aggregation concerns. We borrow from Autor et al. (2013), instrumenting competitive shocks with Chinese imports into nonfocal (but similar) countries, and studying R&D expenditures and cite-weighted patenting among U.S. manufacturing firms. We use scope data (from Hoberg and Phillips forthcoming) as a measure for the breadth of product markets that a firm operates in, to proxy likelihood of aggregation concerns in firm-level innovative responses. The competition-innovation empirical relation in our data is sensitive to the extent of potential aggregation problems. The lowest scope firms show much clearer relations than the highest scope firms. We conclude that (even) firm-level estimation of the competition-innovation relation is likely compromised by aggregation issues.

We then turn to the pharmaceutical sector to reexamine the competition-innovation relationship. We choose this setting to avoid both aggregation problems and difficulty measuring distance to technological frontier. Pharma is ideal for several reasons. First and foremost, pharmaceutical data are available at the product/project level, with each project targeting a specific product market (therapeutic area). This enables measurement of innovative activity (as well as competitive environment), with the granular detail necessary to avoid aggregation challenges. Second, pharmaceutical research and progress is well-documented and carefully regulated. The two combine to help identify precisely targeted innovation responses by rivals, to product (i.e., therapeutic) market competitive-position shocks, as well as measurement of technological distance to frontier.

Specifically, we study shocks to the competitive ordering of treatments in therapeutic areas. On

[3] As we will describe in Section 1.3, measuring distance-to-frontier in standard settings is complicated by price effects. This complication is absent in pharma setting, so we defer a discussion of our control for this to that setting.

July 9, 2012, the Food and Drug Administration (FDA) introduced a new expedited evaluation pathway named the Breakthrough Therapy Designation (BTD) program. It is designed to facilitate and accelerate the approval of early-stage therapies that have demonstrated substantial improvements over available treatments in a given therapeutic area (aka disease indication).[4,5] The BTDs proxy stochastic unleveling of a product (i.e., therapeutic) market, as described in the workhorse model by Aghion et al. (2005).[6] We explore project-level innovation responses by rivals in that specific market, and how these responses are moderated by the ex ante competitiveness of the shocked market. Aghion et al. (2005) predict an inverted-U response, with innovation increasing when the unleveled market is ex ante less competitive and decreasing when the unleveled market is ex ante more competitive.

This approach offers several advantages. The primary one was noted above: we can explore project-specific innovative activity and thus avoid the aggregation problems that plague most work in this area. Second, by nature, these BTDs represent a step-forward in disease treatment by the recipient drug, and concomitantly a step backward—relative to the new frontier—for rival drugs targeting the same therapeutic area. Thus, distance-to-frontier can be proxied bluntly with BTD versus rival drug projects. In the context of Aghion et al. (2005), the BTD recipient becomes leader and rivals become followers.[7]

Third, we sidestep challenges to identifying *exogenous* variation in competition that would (nevertheless) be expected to influence firms' innovative activities. Instead, we use the setting of Aghion et al. (2005) to test their model's key *mechanism driving* the inverted-U; that innovative activity by firms varies with both the product market's competitiveness and whether that market is "leveled" or "unleveled." Put simply, BTDs identify exogenous shocks to a product market's "levelness" and we test whether competitors in that market vary their innovative responses depending on that market's ex ante competitiveness.

[4] See Sherman (2013), Hermosilla (2024), and Chandra et al. (2024).
[5] We use the terms disease, indication, and therapeutic area interchangeably to refer to the condition that a drug (project) targets. Our preferred term is therapeutic area since it most closely connotes a product market space.
[6] We discuss in Section 2, why it's more appropriate to view BTDs as we do. We also discuss how they are different from a patent (and correspondingly why BTDs do not fit neatly in a patent race setting).
[7] We discuss variation in distance-to-new-frontier that the rival faces, shortly.

Our pharma-based results are presented as follows. We actually begin with firm-level results, to illustrate that even in this setting there can be potential aggregation challenges. First we conduct a simple event study. BTD firms experience significantly positive abnormal stock returns, and rival firms experience significantly negative ones, around BTD announcement dates. Thus BTD events are plausible surprises to the competitors whose innovation responses we seek to explain.

Then we analyze firm-level measures of innovation response by BTD-shocked rivals. We study patenting (with both a simple dummy and cite-weighted patents), and R&D. With rare exception, BTD-recipient firms and rival firms show no different innovative behavior relative to other pharma firms. The fact that BTDs are significant events (proxied by significant CARs among the publicly traded firms), but there is no clear innovation response at the firm level, strongly suggests that reallocation of resources is a culprit; the aggregation problem is present even among pharma firms.

This motivates the remainder of our analysis. We study rival responses to BTD-shocks, at the project level, and specifically where we argue it matters. We proxy the latter in two ways. We fixate on rival responses when the BTD shocks one of their *phase-II* projects. This is in deference to Krieger (2021), who argues for focus on phase-II development stage projects as the critical decision point in drug development.[8] Second, we offer additional analyses of rival responses segmented by the rival's exposure to the shock. Our main methodology is a hazard estimation of project-level progression from phase-II to phase-III, for rivals versus controls.[9] To preview the results, we support the inverted-U prediction of Aghion et al. (2005). We also are able to highlight the limits of their theoretical setting, as the empirical relation changes when accounting for project-level variation in the distance-to-technological-frontier.

Rival phase-II projects that are "shocked" by the receipt of a BTD on a competitor's drug project (i.e., in the same therapeutic area as the rival's project), show higher continuation hazards when the shocked market is ex ante less competitive, and vice versa. The inverted-U appears in our data. Interestingly, even

[8] Phase-II development is a significant decision, expanding human trials and involving much higher expenditure than phase-I. Beyond phase-II, development costs may be similar but uncertainty regarding likely approval is much lower.
[9] Parallel trends analysis suggests exogeneity as they indicate no [anticipatory] rival acceleration of innovation activity in advance of BTD shocks, in that therapeutic market.

with project-level innovation data, we see some evidence that aggregation would be a problem had we explored the effects at the firm level. When we segment our main hazard test by rival exposure to the shock—fraction of their projects in the shocked market relative to overall—the results are slightly weaker in the low exposure subsample. This is where firms have dedicated nontrivial resources to other areas, implying firm-level masking of the relationship.

We then report results to highlight our precision in measuring distance-to-technological frontier for the rival, post-unleveling-shock. When the rival's drug project possesses at least one of the "technologies" that is also used in the BTD drug,[10] they may be construed as closer to the technological frontier (as newly defined by the BTD drug). These drug projects have higher continuation hazards across the board, consistent with the theoretical extension of Aghion et al. (2005) done by Hashmi (2013). Furthermore, these drug projects are especially more likely to reach phase-III when they are an important part of the shocked-rival's project portfolio (high exposure), and when that project resides in an ex ante less competitive market. Overall, our project-level analyses support Aghion et al.'s (2005) inverted U as well as Hashmi's (2013) theoretical extension that incorporates distance-to-frontier, all while controlling for aggregation concerns.

We offer a large array of checks on our results as well as supplementary findings. We address potential anticipation by rivals of an eventual BTD in the therapeutic space, in two separate ways. We continue to find parallel trends in rival innovation leading up to the BTD, even among those BTDs that announced a patent or clinical trial completion beforehand. We also find equal or stronger results in our main hazard if we select those markets that were less likely to see FDA granting of a BTD (based on Hermosilla's [2024] policy exposure measure). We also perform a deeper exploration of patents and the influence of blockbuster drugs within our BTD sample. These serve to increase 'market size' and encourage innovation, without diminishing competition. Our main inferences remain.

Our results are also robust to sampling adjustments. We use tighter matching of treated (i.e., BTD rivals) to control observations, based on both project and firm characteristics; we find robust results when

[10] Drugs often use multiple target-actions or technologies. See Section 2.5.1 for details.

excluding all cancer therapies from our analysis sample; our results hold regardless of whether the first BTD in a market is granted to a biotech or "big pharma" firm; and finally they are robust to restricting our attention to therapeutic markets that are ex ante leveled by construction. On the latter, when a therapeutic area has no approved drugs for sale yet available, this is arguably closest to Aghion et al.'s (2005) neck-and-neck setting. Here too we see the inverted-U (in the competition-innovation) relationship in the data. Finally, we remove drug-project observations which may have been acquired to "kill it" in the spirit of Cunningham et al. (2021) and find similar results.

Another key robustness check is based on measurement of competition. We offer three views: our main one is based on the number of drug projects in a therapeutic area. This is the most readily available measure, enhancing our sample size. We also consider the number of firms operating in the particular therapeutic area in deference to Aghamolla and Thakor (2022). This implicitly weights smaller firms more because they are less likely to have multiple drug projects in a single therapeutic area. We also reverse this intuition by explicitly weighting bigger firms more in our standard hazard. In all of these cases, our conclusions persist. Finally, we are able to obtain drug sales data for a subsample, and thereby construct a sales concentration (HHI) measure. We find two important results. The HHI concentration measure is negatively correlated with our main measure of competition. Second, when using the HHI concentration measure, our main inference persists.

We close our analysis by rewidening the lens and extending our study to other typical finance-outcome variables; acquisition behavior, cash holdings, SG&A expenditures, and leverage. At the extensive margin shocked rivals appear to retrench, unless they were shocked in a particularly important therapeutic market for them (proxied by whether they already have an approved drug for sale in that therapeutic market). They reduce acquisitions and increase cash holdings. By contrast, if they have an approved for sale drug in the (shocked) area, they increase acquisitions, possibly funding with cash—which they spend down—but also with increased leverage. In short, they fight back. The intensive margin yields similar inferences.

We make substantive contributions to several literatures. Primarily, we highlight and overcome two

common difficulties in empirical estimation of the competition-innovation relationship; aggregation problems and estimation of distance-to-technological-frontier. We are also (to the best of our knowledge) the first paper to directly test the mechanism underlying Aghion et al.'s (2005) inverted-U workhorse model. And we are able to do so in a subsample setting that is particularly attuned to a neck-and-neck product market.

We also contribute to a recent spate of papers using pharma data to study corporate behavior at the project level. Krieger (2021), as well as Krieger, Li, and Thakor (2022), examine the impact of negative competitor outcomes—public health advisories (PHAs) and product failures, respectively—on rival project development. Cunningham, Ederer, and Ma (2021) find that firms thwart future competition by acquiring competitors and discontinuing their similar drug projects that were under development. Lo and Thakor (2022), as well as Li, Lo, and Thakor (2021), study changes in law that affect competition and their influence on innovation spending and financing. Kao (2022) studies disclosure decisions on clinical trials outcomes as a function of competition. Chandra et al. (2024) study BTDs, but only the effects on BTD-recipient drug outcomes (time-to-market and safety). None of these papers offers a direct test of the mechanism underlying Aghion et al. (2005), nor do they (all but one) utilize the setting of BTDs.[11]

Finally, we speak to the literature on rival responses to entry threats.[12] Extant work finds mixed evidence on whether incumbents are more likely to deter or accommodate entry. However, none of the listed papers considers within-firm cross-sectional variation in product market competitiveness, exposure to shocks, distance-to-technological-frontier, and responses. We show that these considerations matter.

1. Literature and Evidence of Aggregation and Distance-to-Frontier Concerns

[11] Also, Guedj and Scharfstein (2004) find that smaller biotech firms are more likely to advance lower quality phase-II clinical trials, relative to large pharmaceutical companies. Aboulnasr et al. (2008) study firm-level responses to competitor receipt of priority review designation. Neither of them tests Aghion et al. (2005), and they are both subject to aggregation concerns (estimating at the firm level).

[12] See Walmart entry (Khanna and Tice 2000, 2001), airline entry (Goolsbee and Syverson 2008; Parise 2018; Kwoka and Batkeyev 2019; Ethiraj and Zhou 2019), foreign products entry (Frésard and Valta 2015) generic drug entry (Tenn and Wendling 2014), bank entry (Tomy 2019), and Google's entry into the app market (Wen and Zhu 2019).

1.1 A sample of the literature

We have noted two concerns with measuring the relationship between competition and innovation; aggregation issues and difficulty measuring distance-to-technological frontier. Here, we highlight the development of the literature by summarizing a selection of the work and grouping it into three periods of similarity. Our selection is from an initial Google Scholar search on competition, innovation, inverted-U, and incumbent innovation. We infer aggregation issues based on the papers' estimation of the relationship across multiple countries and/or industries (sometimes product markets). We note where the literature has attempted to measure distance-to-frontier.

Table 1 presents the chosen examples[13] of the extant literature's varying conclusions and how this variation might be driven by the two measurement difficulties.[14] We draw from three non-equal-length periods of research, but that do show within-period commonalities to encourage the grouping. The first period begins with Scherer's (1965) seminal work and ends with Geroski (1991). The relationship between competition and innovation has five different shapes across the sampled papers; zero, positive, negative, U-shaped and inverted-U.[15] The modal outcome is no relationship, and we hasten to point out that the aggregation problem is likely pronounced among those papers, with high counts of units across which the relationship is estimated. We also note that only two papers attempt to measure distance to frontier in their analysis.

The second period surrounds the seminal work by Aghion et al. (2005). Many of the papers use survey data to measure innovation. The conclusions are less variable than in the earlier period, but there is still evidence of aggregation concerns. All but one of the papers studies multiple countries and/or multiple industries (or product markets). Across these we see positive, and negative, and inverted-U relationships

[13] The table's footnotes list the papers, again grouped by period.
[14] The sample of papers behind the table is not purely random. It is a selection from the competition-innovation literature, deliberately varying in conclusions sampled, and also drawing from several markedly different time periods of research. It is designed to highlight variation in conclusions as well as measurement issues that we raise. We buttress this table with more systematic study of the competition-innovation relation in a standard setting (see Table 2 in Section 1.2 below).
[15] Competition is most often a concentration ratio, while innovation is most often based on R&D.

between competition and innovation. Fewer than half of the papers attempt to measure distance-to-frontier.

The final period of the table is more recent (post-2012) and hints at recognition that multiple countries could have varying relationships (perhaps because of differences in regulations or policies across those countries, even for the same industry). The studies are all (but one) of single country settings. Nevertheless, within country the analysis is still cross-industries (or markets), again implying potential aggregation concerns when the estimated relationship is across the sample. Here, too a minority of the papers recognize distance-to-frontier. Only positive and (separately) negative relationships present.

1.2 New evidence of the aggregation problem

Table 1 is admittedly loose and based on a nonrandom sample. We therefore turn to our own analysis of the competition-innovation relationship in the (common) setting of manufacturing firms. Specifically, we study the influence of competition on R&D (relative to assets, both drawn from Compustat) and patenting (cite-weighted, drawn from Kogan et al. [2017], hereafter KPSS). For competition instrumentation, we borrow (both data and approach) from Autor et al. (2013) and estimate the competition-innovation relationship over the 1991–2011 window.[16] We then segment the analysis based on the "scope" of the respondent firm, to ascertain whether aggregation influences the shape of the relationship.[17] In short, it appears so.

We first discuss our 2SLS results of competition's effect on innovation. The instrument is Chinese import penetration in other high-income countries.[18] The second-stage regressions are presented in Table 2.[19] The first two columns of panel A offer full-sample evidence consistent with an inverted-U competition-innovation relationship. Both innovation variables are increasing in the U.S. Chinese Import penetration

[16] Internet Appendix I.D.1. provides details of the first-stage estimation.
[17] We especially thank Jerry Hoberg for provision of his scope data, used in Hoberg and Phillips (forthcoming).
[18] The first stage uses Australian, Danish, Finnish, German, Japanese, New Zealander, Spanish, and Swiss imports from China to instrument for U.S. imports from China. Again, see Internet Appendix I.D.1 for details.
[19] Run at the firm-year level, with firms assigned to industries based on primary four-digit SIC. Instrumented Chinese import competition is at the industry-year level. We include fixed effects for industry, year, and number of segments (from Compustat's segment data) in the second stage.

instrument, as well as decreasing in its square.[20]

We then segment our sample firms by their scope, as defined in Hoberg and Phillips (forthcoming), and rerun the 2SLS. We provide three sorts (allocated to panels A, B, and C): above and below median; upper and lower tercile (with middle tercile removed from analysis); and upper and lower quartile (with two middle quartiles removed). In all sorts, the inverted-U only presents among the lower scope firms. These are firms where the aggregation problem is less likely to occur. There are no significant relationships between competition (level or squared) and innovation, among the high scope firms, regardless of sort.

This strong evidence that aggregation across areas of focus by a business can mask a relationship between competition and innovation, aligns with our concerns about studying broad samples. It is noteworthy that our evidence is based on a U.S.-only sample. When conclusions are reached based on multicountry settings, aggregation problems may be magnified. Extending this argument to cross-industry settings is not difficult, since there is strong variation in regulator treatment of industries that could also influence competitive setting and innovative behaviors.[21]

Furthermore, there can be aggregation issues within industry as well. Empirical papers studying the competition-innovation relationship primarily rely on SIC codes for industry classification (to identify competitive shocks). SIC codes can and often do group firms that are only slightly related. Hoberg and Phillips (2016) study the extent of similarity between the 10-k product descriptions of firms that are classified in the same SIC industry, and find that SIC codes are stale and coarse.

The measurement concerns with SIC codes, when coupled with the breadth of a firm's product market activity, imply potential variation within-industry across product markets, in distance from the frontier. This can exacerbate measurement problems. For example: while Google, Zillow, and Facebook all hold the same four-digit SIC code, each derives revenues from—and lead the technological frontier in—varying product markets. Studying the innovation responses of these firms to heightened competition

[20] All of the second-stage regressions show a low R^2. This is a known characteristic of IV estimation. See Stata for a nice discussion (www.stata.com/support/faqs/statistics/two-stage-least-squares/).
[21] See Kalmenovitz, Lowry, and Volkova (2024) and Donelson, Garfinkel, and Roudini (2024).

without a precise understanding of each of their product's market characteristics and the firm's technological position in it, is challenging. For example, the distance from the technological frontier could help explain why Google shut down its Google+ social media site, Facebook refocused its strategy and resources to combat the rise of TikTok, and Zillow had no obvious changes.

Given the above, we argue that the best setting to avoid aggregation concerns is within-country, within-industry, and preferably offering cross-sectional variation in product markets. This is another benefit to our pharma setting, which in the United States is highly regulated by the FDA with clear and consistent drug development approval processes, but also evaluating many drugs addressing variable diseases. Next, we offer a final-benefit view of our setting that is tied to difficulties estimating distance-to-frontier.

1.3 Incorporating distance-to-frontier measurement concerns

Bloom et al. (2016) note that some countries are closer to the technological frontier than others. This implies potential restrictiveness in the workhorse Aghion et al. (2005) model because by assumption the model limits the gap between leaders and followers to one step. If the countries analyzed vary sufficiently in technological development, cross-country analysis is compromised by not only aggregation but also variation in the extent to which the workhorse model is applicable.

Hashmi (2013) offers this as a potential explanation for the difference between his results of a mildly negative relationship between competition and innovation, and the empirical inverted-U documented by Aghion et al. (2005). In Hashmi's (2013) U.S.-based sample, he argues that manufacturing firms are more unleveled than in the United Kingdom (which is the empirical setting for Aghion et al. 2005). He then adapts their model to allow for greater variation in distance-to-frontier (i.e., more than one step ahead in technology is allowed). The amended model can support a variety of shapes to the relationship: positive, negative, or inverted-U; the shape of the relationship depends on distance-to-technological frontier.

Measuring distance-to-technological frontier is challenging. A common approach is to use revenue-based TFPR, but De Loecker and Goldberg (2014) critique this method as conflating price effects with efficiency. Cusolito et al. (2023) emphasize this flaw as one potential driver of the nonconsensus in the empirical literature on competition-innovation relationship shape. They propose a fix that strips out

markups from plant-level measurement of total factor productivity, to isolate the quantity portion.

Our setting does not suffer from such complications, as we offer two measures of distance to frontier that are bereft of price influence. The first measure is the BTD received on a drug project, which is based on FDA assessment of efficacy in treating a disease. The FDA's policy determination does not consider potential revenue effects. Second, as we will describe later, we can further discriminate within BTD-shocked-rivals, between those that possess one of the technologies used in the BTD drug, and those that do not. In short, we can measure variation in distance to technological frontier, post-shock. This variation aligns with important effects on the shape of the competition-innovation relationship.

2. Drug Industry: Data, Markets, BTDs, and Some Preliminary Results

We require information on company innovation investments by product market, as well as the competitiveness of each market the company operates in. Pharma data offers insights along both dimensions. As Krieger (2021) explains, drugs require testing through multiple stages, eventually climbing through human-clinical trials before FDA approval for widespread use. Each stage of progression is considered a milestone (e.g., moving from phase-I to phase-II of clinical trials) and project milestones data are available through various sources.[22] Each drug *project* also targets one disease indication. We use this information to assign drug projects to product markets. We then determine each market's competitiveness based on the totality of projects targeting that disease.

2.1 Base drug development and manufacturer data

Our drug development data come from Clarivate Analytics' Cortellis Competitive Intelligence™. Cortellis is an industry competitive repository of pharmaceutical innovation and has been used in recent papers (e.g., Krieger 2021; Hermosilla 2021). The full data set of drugs developed for U.S. markets includes detailed development milestone and ownership information on over 50,000 drugs and 100,000 drug projects

[22] Particularly for phases-II and higher in human clinical trials, since FDAAA in 2007. See Aghamolla and Thakor (2021) as well as Kao (2022).

developed by over 10,000 firms.[23]

Our sample analysis period is 2010q1–2021q4. The beginning date allows for about 3 years of data before the first approved BTD, which occurred in late 2012. We retain only drug projects developed for U.S. markets, and we drop those with missing key development dates. We also drop "zombie" projects as defined by Krieger (2021). Finally, we drop all drug projects originated by educational or not-for-profit research institutions.[24] As Section 3 will describe, our primary analysis focuses on phase-II drug projects and their continuation to phase-III. Here, we present the broad sample construction.

Cortellis lists all current and past owners of a drug. It further indicates whether a change in ownership has occurred (drug owner acquired, spun off, divested, restructured, or had operated as a subsidiary under another firm). However, Cortellis does not always identify the dates on which ownership has changed. To establish drug project ownership dates across all firms involved in developing a drug project, we match the Cortellis data to SDC Platinum's M&A data.[25]

We combine drug and firm data to create a panel with observational level of drug-project-quarter. We allow a drug project's characteristics (e.g., patent coverage status, stage of development, etc.) and ownership to change over time. The panel includes 67,912 drug projects developed by 7,486 firms from 2010q1 through 2021q4, or 1,884,400 drug-project-quarter observations.

2.2 ICD-10 therapeutic areas

A drug indication is the medical condition that a drug is meant to treat. Cortellis reports drug projects by indication. However, these indications are descriptions that can come from multiple data-sources driving Cortellis' data collection process.[26] These descriptions of the same medical condition are

[23] A single drug may be used in multiple projects, with each project targeting a different medical condition (i.e., indication). We therefore define a drug project as a drug-indication combination.
[24] These institutions have different sources of funding (e.g., NIH), and therefore, different incentives to innovate. Drug projects originated by these institutions are only included once they are licensed to a corporation.
[25] Our specific ownership assignment procedure is described in Internet Appendix I.B.
[26] Cortellis collects drug development information from conferences, firm financial statements, and public resources (e.g., ClinicalTrials.gov).

not always consistent across such sources.[27]

To identify potentially competing drug projects, we perform a grouping analysis. We map Cortellis indications to the 10th revision of the International Statistical Classification of Diseases and Related Health Problems classifications (herein ICD-10 codes) at the second subchapter level.[28] These codes define a therapeutic market. Then we identify all drug projects targeting indications inside the same ICD-10 market, as competing ones. Our final count of unique ICD-10 therapeutic markets is 1,580.

2.3 Therapeutic market competitiveness

We define our competition measure as the number of drug projects (in any stage of development) in an ICD-10 market, in each quarter.[29] We choose this project-count-based competition measure over other sales-based competition measures for several reasons. First, it allows us to examine the overall level of development activity within a therapeutic market. Since drug projects often span several years before regulatory approval, *sales-based* competition measures do not incorporate information on a significant portion of the development activity. This is particularly relevant for firms developing not-yet-approved projects but that are expected to compete for pharmaceutical sales upon approval.[30] Second, sales-based competition measures are subject to measurement error since sales are reported at the aggregated drug level, and most approved-for-sale drugs target several markets. This complicates the calculation of the overall contribution of each market to the drug's total sales. Finally, drug prices are normally reported on a list price basis and do not adjust for rebates, further complicating measurement of drug revenues within a therapeutic market. In short, sales-based measures of market competitiveness are noisy.[31]

---

[27] For example, the two Cortellis indications "hsv infection" and "herpes simplex virus infection" refer to the same medical condition.

[28] We consult a clinical pharmacist to find concordance between Cortellis indication names and the ICD-10 diagnostic codes at the second subchapter level. Internet Appendix I.A provides details.

[29] See also Krieger (2021) and Li, Lu, and Taylor (2021).

[30] Several papers show that firms pay particular attention to competitors' projects under development (e.g., Kao 2022; Cunningham et al. 2021).

[31] Nevertheless, our main result is robust to using an alternative—much noisier—sales-based HHI concentration measure calculated from Cortellis sales data. These results are reported in Table B.7 in the appendix. Furthermore, Internet Appendix Section I.D.2 provides details on the construction of this sales-based concentration measure and shows that HHI (from noisy data) is significantly negatively correlated with our main competition measure. This lends further credence to our use of the *more precise* project-count measure of competition.

2.4 BTD program salient institutional characteristics

The BTD program specifies two criteria for award: the recipient drug must target serious or life-threatening conditions; and it must demonstrate substantially better treatment effects than existing therapies. The latter is stringent. Submitted results from phase-I or phase-II clinical trials are carefully assessed by FDA staff. Preliminary clinical evidence should show a clear advantage over available therapy. The closest other FDA program for expediting drug projects the Fast Track program, requires only mechanistic rationales instead of clinical results to support claimed supremacy[32] (see Hermosilla 2024).

Another key element of the BTD program is its early-decision setting. Figure 1 illustrates this in the context of the drug development process. BTDs may be requested as early as concurrent with an Investigational New Drug (IND) application, and typically before the end of phase-II. The timing is important because it allows for a meaningful impact of BTDs on approval speed, which is one of the goals of the program. This further implies that widespread knowledge of clinical trial outcomes (before the BTD announcement) is unlikely, supporting the surprising nature of the announcement.[33]

Third, BTD-recipient drug projects are much more likely to receive FDA approval (to market the therapy) and do so faster than other drug projects. Our data show this (see Internet Appendix Section I.C.4), as do Hermosilla (2024), Hwang et al. (2018), and Chandra et al. (2024).[34] Taken together, these characteristics align with Aghion et al.'s (2005) characterization of stochastic unleveling in a product market and the BTD recipient becoming a leader (with rivals as laggards) – one step ahead and redefining the technological frontier.[35]

---

[32] Further evidence of BTD exclusivity is seen in the lower success rate on applications. While about 65% of FTD applications are approved, only 35% of BTD applications win designation.

[33] Nevertheless, our results are robust to sampling on BTDs that were preceded by clinical trial completions or patents; see later. Both types of pre-BTD events might be viewed as undermining the presumed lack of anticipation bias, but our analysis of this subsample suggests otherwise.

[34] Some of this is undoubtedly the preferential attention given to BTD drug projects; while the BTD program is the fourth addition to the FDA's expedited approval pathway programs, it tops the ranking in terms of where FDA resources are prioritized (Senior 2013).

[35] So too is the evidence we present in Internet Appendix I.C.3 detailing the views of patients, doctors and the industry, of BTD-awarded drugs. In summary, physicians are more likely to prescribe approved BTDs relative to alternative therapies, and patients are more likely to request them. Since demand for pharmaceutical products is mostly driven by physician office visits, BTD drugs often become the sales leader in the therapeutic market they target.

A prominent example also supports the view that BTDs "unlevel" the product (i.e., therapeutic) market. In 2013, the FDA awarded Gilead Science's Harvoni with a BTD for the treatment of Hepatitis C (Hep-C). Prior to 2013, there were over 10 FDA-approved therapies for the treatment of Hep-C, most of which used a technology known as Interferon. Harvoni's novel technology transformed the Hep-C landscape. Whereas previous therapies (using interferon technology) cured around 45% of the patient population and required 6–12 months of treatment, Harvoni cured over 95% while simultaneously reducing the treatment to 12 weeks. Harvoni, which achieved full FDA approval for marketing in 2014, had extended the technology frontier of the Hep-C market and rendered previous technology inferior. This market transformation also changed the drug development decisions of rivals; more than 30 projects were initiated after 2013 (i.e., post-BTD), and over half shared at least one target action (i.e., technology) with Harvoni, while only one used the Interferon technology.

2.4.1 The difference between BTD awards and patents.

A natural question is whether BTDs are like patents in their potential influence on the competitive ordering in a product (i.e., therapeutic) market and the corresponding incentives of rivals to innovate. We argue they are different for several related reasons. First, BTD-awardee drug projects can have one or more patents "within it" but that were granted earlier in the development process. These patents are typically narrow, focusing on either active ingredient or formulation or delivery method.[36]

Since patents only protect the narrow item, a drug can only be fully protected by patent against another identical-composition drug, and only until the patent(s) expire(s). In other words, patent protection is against generics (aka within-patent competition; see Lichtenberg and Philipson 2002). In actuality, between-patent competition is quite common in the pharma industry, with a lower bound estimate of roughly 60% on the WHO's essential list.[37] See Table I.E.3 in Internet Appendix I.E.3., for three prominent examples. Thus, competition is not "shut down" by a patent, nor is innovation an unattractive response. We buttress this conclusion with analysis of new drug project initiation activity in BTD-awarded markets. When

[36] See Lo and Thakor (2022) for a nice review.
[37] See Aronson and Green (2020), where lower bound is inferred from their classification of me-too drugs.

the shocked market is less competitive, initiations spike.[38]

Also, in our robustness analyses we provide a deeper exploration of patenting, competition, and market size around blockbuster drugs' original BTD receipt. Blockbuster drugs might be viewed as closest to patent race winners with winner-take-all outcomes. However, our data suggest otherwise; even in this subsample, we find little evidence of rival "give-up." Rather, innovation continues, and competition does not appear to decline. See Section 5.2.1 for details.

Finally, patents are not necessarily the best measure for innovation because of two related measurement issues. First is that companies may invest resources in R&D, for example, to attempt technological forward progress, but doing so may not always work.[39] One explanation for this can be found in Farre-Mensa et al. (2020), who find that patent request success can depend on the leniency of the examiner. This further discourages the use of patents as a sole measure of innovation.

2.5 BTD event data, recipients, and rivals

We obtain BTD drugs and grant dates from the Friends of Cancer Research (FOCR) website.[40] The site identifies each BTD drug's name, the announcement date, the sponsoring firm and the indications for which the BTD was granted. We manually match each BTD award to its corresponding drug project in the Cortellis data.[41] If a BTD is granted to more than one drug or more than one firm, we treat each as a separate BTD. Finally, we drop (8) BTDs that were rescinded, from our sample. The final sample of BTD events is 426 unique designations, awarded to 487 drug projects in 206 ICD-10 markets.[42] Our sample comprises 189 BTD-receiving firms, 141 of which are public (48 private). Most BTDs are awarded to larger publicly traded firms and to firms with already-FDA-approved drugs on sale in at least one market.[43]

---

[38] See Figures I.E.4 in the Internet Appendix.
[39] Aghion et al. (2005) implicitly note this when they explain their reasoning for studying patents in their empirical work. It's because R&D data are not readily/completely available for U.K. firms prior to 1990.
[40] https://www.focr.org/breakthrough-therapies
[41] Internet Appendix I.C.1 provides details on this matching process and the cross-validation with other data sources.
[42] Note that the same BTD can be awarded to several drug projects or to several firms.
[43] Internet Appendix I.C.2 provides both time-series and cross-sectional visualizations on BTD awards. Figure I.C.2.A displays the distribution of awards by year. Figure I.C.2.B presents the distribution of awards by therapeutic market. The latter shows that most designations were granted in the cancers and neoplasms markets (about 47% of all awards). This is not surprising given that the program requires designated drugs to target serious or life-threatening conditions. Furthermore, most drugs under development target some type of cancer (e.g., 33% of our sample drugs).

We define a rival as any firm that is actively developing at least one drug project in the BTD-shocked ICD-10 market, but who does not have a BTD-awarded drug in that market.[44] We focus the bulk of our analysis on rivals' drug projects and their development.

2.5.1 Varying the type of rival based on technological distance to frontier.

We are able to further differentiate between rival drug projects that are likely closer to the newly defined technological frontier [per the BTD drug], and those further away. We do so by paying particular attention to the "technologies" (aka "target actions") of drugs (which Cortellis provides). Drugs often have more than one target action. These are the mechanisms through which a drug produces its effect; what it does inside the human body - like attaching or binding to a particular inhibitor. Different drug projects might vary in the inhibitor targeted, but there can also be overlap. An example illustrates.

Harvoni works inside the human body by targeting the NS5B Polymerase inhibitor and also the protein NS5A inhibitor. A competing drug (owned by Abbvie) works by targeting those same two inhibitors as Harvoni but also a third target, namely, the NS3 Protease inhibitor.[45] Abbvie's competing drug, which is in the same therapeutic market (trying to treat the same disease), also shares at least one technology. Therefore, we label it as "same market same technology" or SMST (see later as well).

2.6 Stock price reactions to BTD events

To establish that BTD grants are a surprise, that is, positive for BTD firms and negative for rival firms, we conduct event studies around BTD announcements. The sample's observation level is firm-event-date and includes BTD-recipients, rivals, and controls.[46] BTD recipients belong to that group only for the event(s) where it receives a BTD. Rivals are defined in detail below. Control firms do not have any drug projects residing in the BTD drug's ICD-10 market, on the event date.

We calculate abnormal returns using a market model with parameters estimated over [−271, −21], relative to the BTD grant announcement date. The abnormal event return (CAR) is calculated over the

[44] It is feasible that a rival in one market may possess a BTD drug in a different market (where we would not include them in the set of rivals).
[45] The drug is Paritaprevir + Ritonavir + Ombitasvir. See Table I.A.3 in Internet Appendix I.A for details.
[46] All firms in this analysis must be publicly traded, somewhat reducing our sample size for this test.

three-trading day window [-1, +1] relative to the same date. We drop observations where the firm had other important corporate events around the BTD announcement.[47] We winsorize CARs at the 1% and 99% levels for analysis and reporting. The final sample includes 352 BTD announcements, 12,712 rival firm-dates, and 160,442 control firm-dates.

We define three types of rivals at the firm level (on the event date). First, we define a general BTD rival as any firm with a drug project in a market that saw the BTD awarded to a competitor's project. We then define two within-rival groups: SMST rivals (abbreviation for Same Market Same Technology) are rivals (those with a project in the market that experienced BTD entry) with that project sharing a target action (i.e., technology) with the BTD drug; SM rivals as those rivals who are not SMST.

Table 3 presents ordinary least squares (OLS) regression results of the 3-day abnormal event-returns (CARs) on variables that capture a firm's status in the shocked therapeutic market. Column 1 confirms that BTD announcements are good news for recipient firms (2.6%) and bad news for rival firms (-0.1%), both statistically significant relative to control firms. Column 2 illustrates that the negative experience by rivals is restricted to those without a technology (on their shocked drug project[s]) that also is found in the BTD recipient drug project; the coefficient estimate on *SMST rival* is insignificant while the coefficient estimate on *SM rival* is negative (-0.2%) and marginally significant. The effect on BTD firms remains the same (obviously). Column 3 restricts the sample to just rivals, to explore the intensive margin of SMST. Compared to SM rivals, the SMST rivals experience significantly higher event returns (1.1%). Overall, we conclude that BTD events are surprises.

2.7 Firm-wide innovation responses to BTD shocks

Given significant stock price reactions among rivals to the BTD recipient, we ask whether the rival responds with innovative activity measured the typical way. Specifically, we study rival patenting and rival R&D—both at the firm level—after the BTD shocks at least one of the rival's drug projects. The firm-level

[47] Because of the large sample, we restrict our search to observations with CARs in the top and bottom 5% of the distribution. We match these observations to data on M&A (from SDC Platinum), and to earnings announcements (from IBES), to ensure we identify either confounding merger announcements or earnings events. We drop firm-date observations that matched.

focus is deliberate, to highlight that aggregation concerns exist within pharma-samples, and that we attend to in our main (Section 4) results.

We form a panel of firm-years from BTD, rival, and control firms. BTD firms are those that receive a BTD on one of their drug projects. This "assignment" to category is for the four quarters following the receipt. Rival firms are those who have at least one drug project in the same therapeutic market that the BTD was granted in. Here, too the "assignment" is for the four quarters following the BTD. Control firms are those that do not have any drug projects in the BTD recipient market (again over the four quarters following BTD).

We study patenting and R&D as two standard proxies for innovative activity. Patent data come from KPSS and have been measured at the firm-quarter level with two variables: an indicator (Patent Dummy) equal to one in any quarter the firm had a patent, and Citation-Weighted Patents across all patents a firm received in that quarter. R&D is standard from Compustat and scaled by total assets. There are 35,951 firm-quarters with patent information available and 25,901 firm-quarters with R&D data.[48]

Table 4 presents OLS estimates of each of the three innovative responses to BTD shocks. There are three columns of results for each innovation variable (patent dummy, cite-weighted patenting, R&D, respectively). The first column of each dependent variable analysis reports effects of the indicators for being a BTD firm or a rival, relative to a control firm. In column 1, BTD firms show marginally reduced likelihood of patenting in the four quarters after receipt, while rival firms show no effect. Continuing in columns 4 and 7, the weakness is even more obvious with neither BTD recipient firms nor rival firms showing changed cite-weighted patents or R&D relative to controls. These results, particularly among rivals in the face of significant stock price declines to the BTD event, suggest reallocation of resources and an aggregation problem in measuring firm-level responses.

The second column under each dependent variable separates the effects of SMST rivals from SM rivals (both relative to controls). Patenting—the indicator in column 2 and cite-weighted in column 5—

[48] When Compustat reports R&D as missing, we typically assign it a value of zero, unless more than 50% of the observations for that firm (in our sample) are missing, in which case we code it as missing in our data.

declines among SMST rivals relative to control firms, but there is no difference in patenting between SM rivals and controls. We infer that SMST rivals reduce their patenting (and the research resources that go into it) because they possess a technology that just received a credible outside signal of value. While this is only one interpretation, we do find project-level evidence later that suggests SMST rivals "double-down" on their technology that was part of a recent BTD event. We add that R&D shows no difference between rival type (either SM or SMST) and controls.

Finally, it's notable that at the intensive margin (within rivals) there is no difference between SMST and SM in all three innovation proxies at the firm level. Overall, the dearth of firm-level effects of the BTD on rival innovation measured with patenting or R&D, strongly suggests aggregation concerns can be present even among pharma firms. This motivates our turn now to project-level analysis.

3. Project-Level Analysis: Empirical Design, Development Hazards, and Parallel Trends

This section lays out our main testing approach. Section 3.1 explains the focus on phase-II projects and their graduation to phase-III to proxy innovation, and it describes the analysis sample. Section 3.2 presents the hazard model. Section 3.3 presents time trends in the development rates of BTD-shocked phase-II projects, relative to control (i.e., nonshocked) projects, around BTD events.

3.1 Phase-II to Phase-III development continuation: Data and motivation

Our main analysis relies on the development of drug projects from phase-II to phase-III to proxy innovation. Our reasons mirror Krieger's (2021). First, phase-II is the initial test of a drug's efficacy in humans, requiring significant capital investment.[49] The magnitude of resource dedication aligns with Aghion et al.'s hazard rate of innovation rising in investment amount. Second, phase-II projects have much higher levels of uncertainty relative to phase-III projects.[50] Given such high uncertainty, the information content of a BTD event at this development stage is large. Third, firms are legally required to report their

[49] On average, phase-II projects cost between $13 million and $80 million, whereas phase 1 projects cost between $4 million and $8 million (Krieger 2021).
[50] Hay et al. (2014) report that only 16% of phase-II projects are eventually approved versus a 50% approval rate of phase-III.

phase-II trial results in a timely fashion, providing a more complete characterization of competing projects and innovation outcomes within a therapeutic market.[51]

Our data panel formation begins with all projects that report phase-II trials at any point in time between 2010q1 and 2021q4 (inclusive). We then identify the subset of phase-II projects that reside in the same ICD-10 market that experiences BTD entry *at some point* in our sample period. Broadly speaking, these are the potential rival projects.[52] Rival projects are then selected in two distinct ways reflecting time-series criteria. In the broadest selection, all potential rival projects owned by firms that did not have a BTD of their own in that market, are designated as rival projects starting on the BTD event quarter and until the end of the sample. The corollary subsample of "never shocked" firms is our control set. Our main tests are based on this broad selection. Our stricter sampling (noted in footnote 5) is of these rival projects for up to 12 quarters after the BTD event quarter. In both cases, nonrival projects (never-shocked, preshock, or after the post-shock multiquarter window closes) serve as controls.

Table 5 presents summary statistics for the full sample of phase-II drug projects. There are 12,038 projects developed by 2,319 firms in 992 ICD-10 markets from 2010q1 to 2021q4. The observation level in the sample is project-quarter and the final panel consists of 915,736 observations. We then divide the sample into two groups; rival projects that eventually experience BTD shocks, and control projects that are never shocked. Panel B further partitions the rivals-sample by whether the rival phase-II (shocked) project has at least one technology that also is in the BTD, or not. In other words, we separately list characteristics of SM versus SMST projects in panel B.

Three key observations emerge from panel A. BTD-shocked projects are generally less likely to continue phase-II development relative to control projects. This is especially the case in high competition markets. Third, about 77% of BTD-shocked projects fall in high competition markets, whereas only about

[51] The 2007 FDAA Act required firms to report the findings from phase-II and phase-III (but not phase-I) trials no later than a year after their completion. Firms that delay reporting beyond this window are subject to civil monetary penalties of about $10,000 per day.

[52] We drop any phase-II projects of BTD-recipient firms that reside in that BTD-receipt market. We do so to mitigate the confounding effects of BTD awards on the recipient firm's innovative activities.

one third of control projects target these markets. This last finding is expected since BTD designations are mostly awarded to the more competitive indications that are serious or life-threatening.[53]

Panel B also provides important univariate patterns. Primarily, we take note of markedly higher continuation rates (from phase-II to phase-III) among SMST rivals than among SM rivals. When the rival project shares at least one of the technologies used in the BTD drug, this appears to encourage development effort. We also see that the shocked market's competitiveness is related to continuation; the graduation rate is higher when the rival's phase-II project resides in a market that is less competitive. This pattern persists across types of rivals (SM vs. SMST).

3.2 Hazard methodology

We label our key independent variable *BTD shock*, which serves as our proxy for a therapeutic market's unleveling. It is an indicator variable set equal to one for rival projects starting on the BTD grant quarter and continuing until the end of the sample and zero otherwise.[54] Our main dependent variable *Development dummy* is also an indicator, set equal to one in the quarter that a drug project graduates to phase-III, and zero as long as it remains in phase-II.

We follow Krieger (2021) in using a hazard model to estimate the effect of shock events on phase-II project development decisions. A hazard model accounts for binary outcome variables (reaching phase-III or not), variable response times (to reach phase-III), and right censoring (drug development typically lasts several years, implying firms may continue development after the end of our sample period). We use the Cox proportional-hazards model with the *Development dummy* as our success event. The analysis time is the number of quarters since the start of phase-II for that drug project. Our base specification is:

$$h_{ij}(t) = h_{0j} \cdot exp[\beta_1 * BTD\ shock_{jt} + X_{ijt}'\boldsymbol{\beta} + \delta_t], \quad (1)$$

[53] Nevertheless, in robustness tests, we confirm that our results are not driven by systematic differences between BTD-shocked—and control—markets. First, we stratify baseline hazards by market in our main tests (more details in Section 3.2). This allows the treatment effects to be computed relative to counterfactuals with highly similar market characteristics. Second, we run our tests using subsamples partitioned on high and low competition levels, where differences in competition levels are much less pronounced. Our inferences persist.

[54] Robustness tests where we shut off the Market Shock indicator 12 quarters after the BTD event yield similar results and the same inferences.

where i indexes drug project, j indexes therapeutic market, t indexes the number of quarters since the beginning of phase II, X_{ijt} are time-varying covariates, and h_{0j} is the baseline hazard rate of Phase-II development. We stratify the baseline hazard by therapeutic market using the more general first subchapter ICD-10 definition. Since we define BTD shocks (and therefore rival projects) and therapeutic markets (and therefore competition) using the narrower second subchapter ICD-10 codes, stratifying the baseline hazards by the first subchapter allows the treatment effect to be estimated relative to three potential counterfactual groups of projects: never-shocked projects in the same second subchapter market that exit before the first BTD shock; projects in the same first subchapter market that is never-shocked; and not-yet-shocked projects in the same first or second subchapter market before the first BTD shock enters.[55] In summary, stratifying our baseline hazards allows us to examine the phase-II development rates of recently shocked projects relative to relevant counterfactual rates of nonshocked projects of the same age, clinical stage and (general) market.[56]

Our main focus is on the *BTD shock* indicator, which captures the effect of BTD entry on a rival project's hazard of advancing to phase III. We are particularly interested in how this effect is moderated by the level of ex ante market competitiveness. We include year fixed effects (the δ_t) and we cluster standard errors by drug project.[57]

3.3 Time trends in phase-II to phase-III continuation rates

Our main tests are effectively difference-in-differences estimations, where the first difference is between shocked and control projects, and the second difference is before and after the shock.[58] Our

[55] For example, lymphoma (with a second subchapter ICD-10 code of "C85-0") has three other related indications: high-grade b-cell lymphoma (ICD-10 code of "C85-10"); primary mediastinal large b-cell lymphoma (ICD-10 code of "C85-20"); and non-Hodgkin's lymphoma (ICD-10 code of "C85-9"). Only the last two indications experienced a BTD shock. This implies that the average BTD treatment effect on the development rates of shocked projects in the "C85-20" and "C85-9" markets is estimated relative to nonshocked projects with the same stage and age, and that reside in the similar first subchapter ICD-10 "C85" market (and therefore share many characteristics, such as the targeted organ, risk factors, and symptoms).

[56] We find stronger results if we do not stratify the baseline hazards at all.

[57] When we extend our analysis to the potentially different continuations of SM versus SMST rival projects, we replace the *BTD shock* variable (in the hazard) with the two mutually exclusive SM and SMST dummies.

[58] The variable, *BTD shock*, is effectively the interactive *Treatment*Post*. In all tests, we include an indicator for markets that are eventually shocked (which would be the *Treatment* variable). *Post*, however, is subsumed by *BTD shock* since only treated projects have a post-shock period (i.e., *Post* is perfectly collinear with *BTD shock*).

identification assumption is that the BTD event is exogenous with respect to innovation. To validate, we construct a test of parallel trends in the response variable – continuation from phase-II to phase-III, between treated and control (both phase-II) projects, prior to treatment. Put differently, phase-II projects in ICD-10 markets that eventually experience BTD entry should have graduation rates *prior to the shock* that are not significantly different from those of control projects; they should only diverge afterward. Even when competitors are aware of the development of a competing drug, they shouldn't be able to predict whether it will receive the designation. However, if BTDs were predictable, rivals would endogenously adjust innovation-oriented spending before the event.

To execute this test across the full sample of phase-II projects, we create an indicator, *everBTDshocked*, equal to one if a project resides in an ICD-10 market that experiences BTD entry at some point, and equal to zero for control projects. We then run a hazard model (of similar specification to Equation (1)), on the graduation rates of phase-II projects, using the interaction of *everBTDshocked* with indicator variables for each of the 5 years before and after BTD entry.[59] We retain the BTD entry year (i.e., year *t*) as our baseline time threshold. To satisfy the parallel trends condition, the coefficients for interactives representing the 5 years preceding the BTD, should not differ significantly from zero.

Figure 2 displays coefficients plotted from this analysis. The caps on each coefficient cover 95% confidence intervals. All graphs of Figure 2 lend support to our identification assumption; graduation rates of projects that are eventually shocked are not statistically different from those of controls pre-BTD, and they only begin to differ significantly afterward. Figure 2, panel A, plots the interactive coefficients using the full sample, that is, before discriminating between the shocked market's ex ante competitiveness. In the first and second year post-BTD, there is little change in continuation rate of shocked relative to control projects. In the third year after BTD entry, shocked projects are about 68% as likely to graduate as control projects, which is a significant difference. In years 4 and 5 post-BTD, the full sample of phase-II rivals

[59] We use year indicators in the interactive, instead of quarter indicators, because phase-II graduation events are exceedingly rare (only 1% of the sample's observations). As a result, some of the quarter-based interactives become noisy, especially in quarters with abnormally higher (or lower) graduation occurrences within groups of shocked and control projects. On the other hand, the graduation events are more evenly distributed across years.

again shows similar continuation patterns as controls.

Figure 2, panel B (panel C), plots coefficients estimated using the sample of projects in ex ante low (high) competition markets, that is, below (above) that of the sample median. The declining hazard in the full sample in year 3 appears to be driven by projects in more competitive markets. In fact, the reduced continuation rate is obvious earlier in year 2 (at the 5% level) and even year 1 (at the 10% level). By contrast, projects in less competitive markets are much *more* likely to continue to phase-III relative to control projects, in the 2 years post-shock. While we offer more complete results soon in Table 6, these figures combine to support the model of Aghion et al. (2005). Post-unleveling, less competitive markets see rivals increase innovation to attempt catch-up while more competitive markets see rivals reduce innovation (following Schumpeter's logic).

Figures 3 and 4 repeat this exercise for rivals split according to whether their shocked phase-II project is SMST or SM (respectively). Again, parallel trends preshock are apparent, particularly in Figure 4 with remarkable stability in the coefficients.[60] The post-shock divergence in continuation in Figure 3 is across the board (full sample, less competitive markets, and more competitive markets). We will see this consistently in Table 6 soon. It supports the encouragement of innovative effort when distance to frontier is smaller (proxied by SMST, in line with Hashmi's [2013] extension of Aghion et al. [2005]). In Figure 4, where rivals' phase-II projects do not have any technology that appears in the BTD drug, the pattern of innovation response to the shock supports Aghion et al. (2005). Continuation is more likely in ex ante less competitive markets, and vice versa.[61]

[60] The stability of coefficients in preshock years (especially Figure 4, panel A) is an artifact of sampling and the stratification of the hazard (which is at the broader two-digit level of ICD-10 market). This captures potentially varying competition levels within a strata. For example, C9 is a broad cancer categorization. Within it there are high-competition markets (e.g., myeloid leukemia) as well as lower-competition ones (e.g., a rarer form promyelocytic leukemia). Given this variation, the hazard compares apples with oranges. To allay this concern, we reestimate the parallel trends (in both 4A and 2A) using the matched sampling methodology that we describe in Section 5.2, to create the estimation sample. The parallel trends show point estimates even closer to zero and with much more variability.

[61] We rerun all of these parallel trend analyses, using OLS, in the Internet Appendix Figures I.E.1 through I.E.3. They show highly similar trends.

4. Project-Level Results

This section presents our project-level results on the effects of BTD shocks on the drug development activities of rivals. The BTD event is treated as an unleveling shock to the therapeutic market that the drug project is targeting. We first examine the effect of these BTD events on phase-II graduation rates of rivals' projects, and how ex ante therapeutic market competitiveness moderates it. Those results present an inverted-U pattern, supporting Aghion et al. (2005). We note the mediating influence of rival exposure to the shock (BTD), proxied by the weight of projects the rival has in the shocked market relative to total rival projects. We also highlight the changing shape of the competition-innovation relation when varying distance-to-frontier, as proxied by whether the rival is SM or SMST.

The section also offers a potentially cleaner test of Aghion et al. (2005) by subsampling on therapeutic markets that are probably closest to neck-and-neck ex ante; those without any approved-for-sale drugs in it yet (only projects under development). Finally, we explore a couple of views on shocked rivals' potential reallocation of resources. First, we look for rival progression of phase-II projects in *unshocked* markets; then we examine drug project initiations of BTD-shocked rivals. We close the section with a brief exploration of finance variables that may facilitate innovation, but that also suggest resource reallocation.

4.1 Phase-II to phase-III continuation rates, influenced by BTD shocks

Panel A of Table 6 presents results from our hazard specification in Equation (1). The results are broadly consistent with the mechanism driving the inverted-U relationship between competition and innovation in Aghion et al. (2005). In column 1 of panel A, we do not include any competition controls and find the coefficient estimate on *BTD shock* is small (0.013) and insignificant. However, column 2 of panel A indicates the importance of therapeutic market competitiveness to rival responses to the shock. The coefficient estimate on *BTD shock* interacted with *Competition* is -0.245 and significant at the 1% level. Among shocked projects, a one-standard-deviation increase in the therapeutic market's ex ante level of competition (which equals 1.49), decreases the likelihood of reaching phase-III by [1-exp(1.49*-0.245)], about 30.6%.

Columns 3 and 4 of panel A separately explore the "two sides" of the inverted-U hypothesized relationship.[62] When competition is ex ante low (column 3), the coefficient estimate on *BTD shock* implies that rival projects in suddenly unleveled markets are 50% more likely to graduate (to phase-III) relative to control projects. This result is consistent with the low competition implication in Aghion et al. (2005). When the unleveling (BTD) shock arrives, laggards (rivals) have an incentive to catch up in less competitive markets; they therefore accelerate their existing phase-II projects (in that market).

By contrast, in ex ante more competitive markets (column 4), the BTD shock discourages innovation. The relevant coefficient (-0.265) indicates unleveling leads to 23% lower likelihood that rival (phase-II) projects continue development (to phase-III), relative to control projects in markets with similar levels of competition. This too aligns with Aghion et al.'s (2005) model. In high competition markets, unleveling discourages rival innovation since post-innovation rents (the returns to catchup) are decreasing in product market competition. In other words, the "Schumpeterian" effect dominates.

We now turn to results that bifurcate our full sample based on the rival's exposure to the therapeutic market where the BTD was granted. Exposure is calculated as the number of projects the rival has in the shocked market, relative to the rival's total number of projects. Columns 5 through 8 run the same analysis as seen in columns 1 through 4 for the low exposure—below-median—subsample. Columns 9 through 12 run the same analysis as seen in columns 1 through 4 for the high exposure—above-median—subsample.

We find that the inverted-U relationship is more pronounced in the high exposure sample tests. In columns 7 versus 11, where ex ante competition is low, the low-exposure-sample coefficient estimate on *BTD shock* is more than 40% smaller than the coefficient estimate on *BTD shock* in the high exposure sample. And in columns 8 versus 12, where ex ante competition is high, there is no influence of the BTD shock on low exposure rivals' innovation, while we see strong discouragement of innovation in the high exposure sample. The weakness of results in the low exposure sample suggests a masking problem if we were to study only firm-level response.

[62] A key benefit to subsample analysis is the removal of interactive variables from a nonlinear model. See Ai and Norton (2003) for a description of the challenges.

4.1.1 The mediating role of distance-to-frontier (SM vs. SMST rival projects).

Panel B of Table 6 explores the different rival reactions to a BTD shock on their phase-II project(s), depending on whether or not the project shares a technology with the BTD-awardee. Those that share at least one technology are labeled SMST and their response profile is expected to follow the extension of the classic Aghion et al. (2005) model provided by Hashmi (2013). The SMST projects align with the model's "very small values of technology gap" grouping.

The results in columns 1–4 support both Aghion et al. (2005) and the Hashmi extension. When the shocked project is SMST, continuation hazards from phase-II to phase-III are significantly raised. As Hashmi (2013) predicts, when the technology gap is narrower, innovation increases. By contrast, when the shocked project is SM (does not share any technology with the BTD-awardee), the inverted-U competition-innovation shape prevails. See especially columns 3 and 4 in panel B, where the coefficients for SM are positive and negative in ex ante less and more competitive markets, respectively. The negative coefficient in more competitive markets is larger in magnitude (reflecting a roughly 35% drop in likelihood of continuation), than in panel A, where we had not controlled for the different treatment effects among SMST versus SM projects. Put differently, the effect of the BTD shock in panel A, column 4, was an average of the different-direction effects of SM and SMST.

4.1.2 A narrower test of Aghion et al. (2005): Markets with no approved drugs for sale.

The effect of an unleveling shock due to a BTD is theoretically most clear when the therapeutic market is ex ante neck and neck. We offer subsample analysis to attempt tighter mapping to this scenario. Specifically, we study therapeutic markets with no approved for sale drugs in it yet, when the BTD is awarded. Rivals with (now-shocked) phase-II projects in these markets respond as before—inverted-U competition-innovation shape—and with apparently more vigor in less competitive markets.

Table 7 presents the results. Panel A eschews delineation between SM and SMST, aligning with panel A of Table 6. We mimic the analysis in columns 1–4 of that table panel as well, just with the narrower sample. Here, we focus our discussion on columns 3 and 4, which study the high and low competition markets separately. We compare across the two tables (full vs. narrow sample).

The coefficient estimate on *BTD shock* in column 3 is more than twice the size in the narrow sample (1.091) compared to the full sample (0.426). When the shocked therapeutic market was ex ante less competitive and more clearly neck-and-neck, rivals' continuation hazards from phase-II to phase-III rise markedly more than in the full sample. In column 4, where the shocked therapeutic market is ex ante more competitive, and again in the neck-and-neck narrow sample, the coefficient estimate on *BTD shock* is significantly negative; the continuation hazard falls. Here, the comparison with Table 6 is more noisy. The coefficient magnitude on BTD shock in column 4 in the narrow sample (-2.210) is nearly 10x larger than that in Table 6 (-0.265). However, the *t*-statistics are similar, suggesting potential outlier effects in the narrow sample. Indeed, we see a much smaller sample size for the narrow (leveled) more competitive set of markets. This is in line with Aghion et al.'s (2005) expectation that more competitive markets tend to remain unleveled.

Panel B of Table 7 delineates between SM rivals and SMST rivals, for the narrow sample analysis. As usual, SMST shocked rivals accelerate innovation, raising continuation hazards from phase-II to phase-III.[63] Comparing the coefficients for *SMST* between Tables 6 and 7 again indicates stronger responses in the narrow sample. We also see this in the coefficients for *SM*, with coefficient magnitudes more than twice the size in the Table 7, columns 3 and 4, than in Table 6.

4.2 Reallocation of resources within rivals

One of our two main theses is that aggregating measurement of innovative response to competitive shocks across various units can mask a relationship. This is a key driver of the benefit of focusing on project-level responses in the pharma industry. Up to now that has led us to focus on rivals' shocked phase-II projects and their continuation (to phase-III) hazards. We eschewed study of other projects held by the rival in order to avoid aggregation or masking. But we can certainly study these other (potential) projects separately. We do so next and continue to find support for the intuition underlying Aghion et al. (2005).

Specifically, Table 8 studies rivals' resource allocation away from the BTD-shocked market. We

[63] The column 4 coefficient, negative and apparently large in magnitude, is insignificant. The estimation effectively fails, with no cases in this subsample that "continue" to phase-III.

do so in two ways. Panel A explores shocked (by the BTD) rivals' development hazards for those phase-II projects that are in markets which did *not* experience a BTD shock.[64] Panel B analyzes new drug initiations by BTD-shocked rivals. Our link to the intuition of Aghion et al. (2005) is to separately estimate the relationships for drug projects that "target" higher or lower competition markets.

4.2.1 Rival phase-II development in never-BTD-shocked projects.

Panel A tests are run on unshocked phase-II drug projects of active rivals (i.e., a different phase-II project was shocked). The observation level is drug project-quarter. We estimate the continuation hazard of these unshocked phase-II projects owned by rivals, to explain likelihood of reaching phase-III [on the unshocked project]. The key explanatory variables are built on two indicators: one for the rival's exposure to the BTD-shocked therapeutic market (i.e., whether the rival was highly exposed to the BTD-shocked market, measured by whether or not exposure was larger than the sample median), and the other for the competitiveness of the BTD-shocked market. In short, we wish to estimate the effects on reallocation of resources (via unshocked phase-II project continuation), of the extent to which the rival was "hit hard" by the BTD.

Shocked rivals show higher continuation hazards on their unshocked phase-II projects that target less competitive markets, and only when that rival was both highly exposed to the BTD-shocked market *and* when that shocked-market was more competitive. Column 1 illustrates: the coefficient estimate on the interactive *HiComp*HiExp* is 0.254 and marginally significant.[65] Put another way, the rival had to be hit *really* hard (high exposure and high competitiveness of the shocked market) to encourage them to reallocate resources toward an unshocked phase-II project in a less competitive market. This reallocation interpretation is also supported by what we know from Table 6 (panel A), that is, that high exposure in a shocked market that was more competitive, led to lower continuation hazards on the shocked project.

On the other side of the inverted U, when the target market of the unshocked phase-II project is

[64] We thank N. Prabhala for suggesting this line of inquiry.

[65] When we control for the two separate indicators of high rival exposure to the shocked market (*Hi_exp*) and whether that shocked market was more competitive (*Hi_comp*), along with the interaction of the two, we observe a similar positive influence of the interaction on continuation hazards. See column 2.

more competitive, there is double-avoidance: shocked rivals eschew innovation even on their unshocked phase-II project, especially when they were highly exposed to the shock and the shocked market was also highly competitive. Recall that they also had lower continuation hazards on their shocked phase-II projects. This raises an important question. Given reduced innovation in both shocked and unshocked phase-II projects when each was targeting more competitive markets, where do these rivals turn?

4.2.2 Drug project initiations of BTD-shocked rivals.

Shocked rivals may also eschew development of phase-II projects overall, and instead dedicate resources to new drug-project investigations (which are typically at the discovery stage). We label these, drug project initiations. To the extent that they absorb resources when the same sort of shock lowers the resource dedication to the shocked project, there would be a masking/aggregation problem with measuring firm-level response. We analyze drug project initiation likelihood as a function of the BTD-shocked drug's market-competitiveness, the rival's exposure to that market, and the new drug's target- market competitiveness. Here, we again restrict our focus to the sample of active rivals. We identify all quarters in which a rival experiences a BTD shock in one of its phase-II projects. Then we examine that rival's drug initiations in the subsequent 4 quarters. The regressions are OLS with indicator dependent variables (i.e., LPM), with firm and quarter FEs. Standard errors are clustered by firm.

Table 8, panel B, presents results from this investigation. In column 1, the dependent variable equals one if a firm initiates any new drug discovery project in that quarter. In columns 2 and 3 we differentiate initiations by the target market's competitiveness. We explain these decisions with the two indicators (and their interaction) that capture the rival's exposure to the shock and the competitiveness of the shocked market, as long as the BTD shocked the rival project within the last four quarters. *HiComp_shock* equals one when the shocked (by BTD) phase-II project of the rival resided in a more competitive market, zero otherwise. *HiExp_shock* equals one when the shocked (by BTD) phase-II project of the rival was in a market that the rival was highly exposed to (greater than sample median), zero else.

Initiations are more likely when the BTD shocked a rival in a high-competition market, and that rival was highly exposed to said market. The coefficient estimate on the interactive *HiComp_HiExp shocks*

is positive and significant. Neither of the individual dummies has that effect stand-alone. In the same circumstances that discourage continuation of a rival's shocked phase-II project, there is greater likelihood of starting a new discovery-stage drug project. Reallocation of resources is present.

Columns 2 and 3 show weaker results, but this may be due to pooling the low and high exposure (to the shock) subsamples. In columns 4 through 6 we subsample the rivals who were highly exposed to the market where their phase-II project was shocked by a BTD. Among these rivals with high exposure, if the shocked market was highly competitive, this especially encourages initiation and *into* less competitive target markets. In other words, when shocked, rivals tend to avoid higher competition and seek to redeploy resources in less competitive markets. This aligns with the intuition of Aghion et al. (2005).

4.3 Financial outcomes

Given our project-level evidence that firms may either increase or decrease innovation in shocked projects, as well as reallocate resources to other projects, this raises questions about the financial mechanisms behind such moves. Table 9 analyzes four financial variables for these rivals and their movement over the four quarters following BTD shock. The variables are *Acquisition* (a dummy set to one if the shocked rival acquired either a whole firm or a drug); *Cash* (scaled by total assets); *SG&A* expenditures (scaled by revenues); and *Leverage* (debt scaled by assets). To preview our inferences, we find that some rivals retrench while others fight back, depending on their current position in the shocked market. Our indicator for this is whether the rival has an approved-for-sale drug in the shocked market.

Panel A of Table 9 explores the extensive margin. Our sample includes shocked rivals and controls. The first four columns do not differentiate between rivals based on whether they have an approved drug already in the shocked market. We find that the BTD shock associates with lower likelihood of acquisition. When we distinguish between rivals that already had an approved for sale drug in the shocked market, they respond differently: they are more likely to acquire a competitor (or a drug), they spend down cash, and leverage rises. By contrast, rivals without any approved-for-sale drugs in the shocked market hoard cash and are less likely to acquire. Rivals with something to protect—sales or profits in the shocked market—fight back, while others retrench.

The intensive margin in panel B—strictly focusing on rivals—yields similar inferences. Those rivals with an approved-for-sale drug in the shocked market are more likely to acquire, they spend down cash, and they show increased leverage.

5. Robustness Tests

We present a battery of robustness checks, from sampling adjustment to calculation of variables and varying methodologies. Our inferences do not change. For space reasons, most of these results are offered in the Internet Appendix. A few key foci, such as anticipation concerns, control sample matching and treatment exclusions, and, finally, competition measurement, have results in the appendix.

5.1 Anticipation concerns

Some of the BTDs in our sample include patents "underneath" them, and some of them had published results from earlier trials. Each of these might be detected by rivals monitoring a particular therapeutic area carefully, and so could enable rival-anticipation of the upcoming BTD.[66] To determine whether this possibility undermines the important assumption of parallel trends in phase-II progression pre-BTD, we repeat the parallel trends analysis that was conducted on our main sample (Figure 2),but focusing strictly on these potentially anticipated BTDs. The results are presented in Figure B1 in the appendix. There is no evidence of anticipation.

Another perspective on anticipation comes from Hermosilla (2024). He argues that the BTD program encouraged drug development in markets with high FDA attention (high policy exposure). These high policy exposure markets experienced an increase in the flow of new drug projects. If rivals anticipate favorable hearings on BTD applications in high policy exposure markets, then parallel trends might be violated in those markets.

We obtain BTD policy exposure data from Hermosilla (2024)[67] and match to our phase-II sample.

[66] We think this unlikely since FDA guidance strongly suggests independent assessment, but we check anyway.
[67] With deep gratitude expressed for sharing.

We divide the matched sample into low and high policy exposure using 50% as the cutoff threshold.[68] We run our main Table 6 tests using the two (high and low *policy-exposure*) subsamples and report the results in Table B.3 in the appendix. Our main results are actually stronger in the low policy exposure subsample. Overall, anticipation does not appear to be a threat to our conclusions.

5.2 Robustness checks with alternative samples

We also replicate our main results using two alternative samples that control for systematic differences between eventually shocked markets and control markets. In the first alternative sample, we match each BTD-shocked project in the full phase-II sample to a single project from a pool of potential control projects. Control projects must satisfy the following criteria. At the drug level, it must have started phase-II development within 5 years of the treated drug. At the market level, it must target a market in the same quartile of competition as that of the treated drug. At the firm-market level, the control firm's exposure to the control project's market must be in the same quartile as that of the treated firm's exposure to the treated project's market.[69] Finally, at the firm level, the size of the control firm developing the control project must be in the same quartile as that of the treated firm developing the treated project. Size is measured as the total number of projects owned by the firm. We then randomly choose one control from the eligible set, to match with the treated project. The final sample consists of 7,623 phase-II projects that correspond to 154,844 project-quarter observations.

We replicate our main tests of Table 6 using the characteristics-based matching sample and report the results in Table B.4 in Appendix B. The results are consistent in direction, but stronger in magnitude and statistical significance. This suggests that our main findings in Table 6 are not driven by systematic differences between shocked and control projects.

Another potential concern with our data is related to the distribution of BTD shocks across therapeutic markets. More specifically, about half the BTD designations in our sample are awarded to

[68] BTD policy exposure is a continuous variable with values between zero and one. A value of one indicates that the market is very likely to experience a BTD award, and vice versa.
[69] As usual, exposure is measured as the number of projects a firm develops in a market divided by the total number of projects developed by the same firm.

projects that target cancer markets. A critical reader may question whether our results are driven by unobservable factors specific to cancer markets. We therefore construct our second alternative sample by dropping all drug projects that target any of the cancer and neoplasms markets, from the full phase-II sample. Projects in these (excluded) markets are identified if the first letter of their assigned ICD-10 code is "C." The final sample of the remaining (i.e., included) 7,485 phase-II projects correspond to 122,901 project-quarter observations. We rerun our main tests using this sample and report the results in Table B.5 in Appendix B. Here, too the results are consistent with our main findings, suggesting that our documented effect is not driven by market-specific factors.

A third sampling discrimination—between BTDs first won by big pharma versus those first won by biotechs[70]—also yields robust results. We look to see whether big pharma winning the first BTD in a market discourages others from innovating *more* than when a biotech gets the first BTD. We do not. In Table B.6 in the appendix, we show inverted-U results in both subsamples. If anything, discouragement is *more* pronounced in the subsample where a biotech received the first BTD in that market.[71]

Finally, in deference to Cunningham et al. (2021), we examine the potential influence of "killer acquisitions" on our results. We remove a subsample of drug projects that were acquired, and then rerun our Table 6 analysis. Panel B of Table I.E.2 (in the Internet Appendix) presents the results. They continue to show our usual results that support the inverted U. Panel C, continuing with this nonacquired sample, also shows the strong positive effects of SMST.[72]

5.2.1 Separate consideration of blockbuster drugs.

When a drug is a "blockbuster," it has the potential to affect our inferences in a few ways. First, it aligns with popular notions of why drug companies are willing to spend vast resources on R&D, that is, to obtain sufficient profits on the blockbuster drug project to cover the cost of research overall. But this also

[70] Firms with no approved-for-sale drugs yet.
[71] This is easiest to see when comparing columns 3 and 4 with corresponding columns 7 and 8.
[72] Panel A of Table I.E.2 illustrates results consistent with Cunningham et al. (2021), wherein the *acquired* projects that overlap with the bidder's drug portfolio are less likely to graduate to phase-III.

encourages the behavior of follow-on patenting to extend protection from generics.[73] If pharma firms can expect near-monopoly rents from BTDs that become blockbusters, this could encourage ex ante entry where demand for a therapeutic solution is high, and further explain the post-BTD decline in innovation we document in our main (Table 6) results among rivals that did not receive the BTD. This would contrast with more-intense-competition explanation for the right side of the inverted U.

To knock down this potential alternative, we offer several analyses. The first was already provided in our separated analysis of low and high policy exposure subsamples (see Section 5.1). The above concern would likely be concentrated in the high policy exposure subsample; but we show that our results are robust to focusing on the low policy exposure subsample too.

The second approach is to conduct a deeper analysis of BTD drugs that eventually become blockbusters. We identify a blockbuster based on the industry standard definition of at least $1 billion in annual revenue. Of our 487 BTD-awardee drug projects, we have 245 with FDA approval-to-market the drug and actual sales data from Cortellis. Of these, 100 meet the blockbuster criterion. We then perform both market-wide analysis and rival phase-II project development hazards around this sample.

For the market analysis, we form a (therapeutic) market-quarter-level data set that allows us to explore six different measures of therapeutic-market activity over time. These are drug initiations; drug approvals; market competitiveness (main definition which is a count of the number of drug projects); market concentration (a sales-based measure described in Section 5.3 and Internet Appendix I.D.2); total market sales; and number of patents. The independent variables are a dummy for post-BTD, a dummy for blockbuster, and the interaction of those two variables. We include calendar quarter fixed effects and therapeutic market fixed effects. We cluster standard errors by therapeutic market.

We present these results in Table B.10 in the Internet Appendix. They point strongly toward market expansion, especially post-BTD for blockbuster drugs. The expansion of the market seems to counteract the endogeneity (of ex ante market competitiveness) concern tied to our observed decline in innovation

[73] This is not "full protection" from competition. See our discussion in Section 2.4.1.

(phase-II to phase-III progression in the hazard) among ex ante more competitive markets. The results that initiations, and approvals, and number of drug projects, and therapeutic market overall sales, and number of patents, all increase, suggest that there is less "give-up" [by rivals] after a BTD than feared. Noteworthily, the coefficient estimate on the post-BTD*blockbuster interactive in the market concentration (HHI) regression, is insignificant ($t = 0.468$). The therapeutic market does not become significantly less (nor more) competitive. In short, we conclude that even among blockbusters, we do not see declines in either patenting or competition in those therapeutic markets post-BTD.

To buttress our conclusion that there is more to our main evidence than potentially endogenous effects tied to winner takes all (most likely among blockbuster drugs), we rerun our main hazard separately for blockbuster and non-sub-samples. See Table B.11 in the Appendix. The inverted U persists in both subsamples but appears stronger in the nonblockbuster sample. Notably, the coefficient estimate on *BTD shock* in the high ex ante competition blockbuster subsample is weak. Precisely where concerns about an alternative explanation might present, we don't see evidence of that alternative in the data.

5.3 Robustness checks with alternative competition measures

Product market competitiveness plays a first-order role in our tests, motivating investigation into the robustness of our results using alternative measures of it. We offer three such alternatives: a sales concentration (HHI) measure; two firm-count (as opposed to project-count) within-market measures, one equal-weighted and the other value-weighted. Our Table 6 results are robust to all three.

Notwithstanding the limitations discussed in Section 2.3, we construct the drug sales concentration (HHI) measure in each therapeutic market, per the details provided in Internet Appendix I.D.2. There too (in Table I.D.1.) we report its negative correlation [because concentration is the inverse of competition] with our standard project-count measure of therapeutic market competitiveness. However, we "promote" the results from rerunning our Table 6 using the HHI measure, to Table B.7 in the appendix. Our inferences are unchanged. There is an inverted U in the competition-innovation relationship, where higher competition is proxied with lower concentration in sales (HHI). More competitive (less concentrated) markets associate with lower hazards on rivals' BTD-shocked phase-II projects in that area, and vice-versa. These effects are

clear in the SM subsample and we continue to see the same mediating effects of SMST projects.

Tables B.8 and B.9. then presents robustness results using the number of firms within a market as the competition measure. We try two versions of "counting firms," one equal weight (Table B.8) and one value-weight (Table B.9) based on firm size-rank. This is in line with Aghamolla and Thakor's (2021) approach. The results again support our Table 6 inferences. Overall, our findings are not driven by the choice of proxy for market competitiveness.

5.4 Other robustness checks

We consider alternative methodologies for estimating the shape of the competition-innovation relationship. We rerun our Table 6 hazards but using either OLS or Logit, and offer those results in Tables B.1 and B.2 in Appendix B. They report robust results.[74]

We also consider a nonparametric approach. We form 100 competition percentile bins for therapeutic market competitiveness (using our usual definition); then simply explore the percentage of phase-II projects that graduate to phase-III, in each bin. Results are pictured in Internet Appendix Section I.E.2 and Figure I.E.5. The shape of relationship is inverted U when looking strictly at SM projects, with a turning point around the 23rd percentile. The picture is less clear when estimated over all rival phase-II projects hit by a BTD, and all projects overall.

6. Conclusions

We study the competition-innovation relationship from a new perspective, recognizing two thorny measurement issues that compromise observed shapes. One is that studies likely aggregate across units that likely have different competition and innovation incentives; the other is that distance-to-technological frontier is hard to accurately compute. We illustrate how these have influenced the literature, including with new results. We then proceed to offer a different setting and set of tests designed to circumvent both

[74] Unlike the hazard model, which controls for right censoring, OLS and logit models do not. We control for the right censoring nature of our data by dropping all phase-II projects that started development after 2019q4 (since phase-II development takes an average of 2 years, and our sample ends in 2021q4).

complications.

We specifically study the pharma industry which has both project-level granularity in data on competitiveness and innovation, and carries unique information on distance-to-frontier. We use this data to test the driving mechanism underlying the workhorse model in Aghion et al. (2005), as well as the theoretical extension by Hashmi (2013). We support both.

FDA grants of Breakthrough Therapy Designations to particular drug projects are shocks to the therapeutic (disease) area that the drug targets. Rivals who are also working in that area respond to this "unleveling" in a manner consistent with Aghion et al. (2005); they increase innovation when the shocked market was ex ante less competitive and reduce innovation when the market was more competitive. The inverted U presents in our pharma data. We further show that when the rival's shocked drug project shares one of the technologies found in the BTD, the shape of the relationship changes. The shared technology increases innovation, consistent with Hashmi (2013).

Firms also reallocate their innovative efforts. They pursue new projects and do so when the target market is less competitive. The documented innovation adjustments may also involve resource adjustments, and we find evidence of retrenchment versus fight-back that depends on the firm's project portfolio. Future work may also seek to explore changing incentives with pay, in order to facilitate desired fight-back when appropriate.

Code Availability: The replication code is available in the Harvard Dataverse at https://doi.org/10.7910/DVN/SDA0ZX.

References

Abola, M. V., and V. Prasad. 2016. The use of superlatives in cancer research. *JAMA Oncology* 2:139–41.

Aboulnasr, K., O. Narasimhan, E. Blair, and R. Chandy. 2008. Competitive response to radical product innovations. *Journal of Marketing* 72:94–110.

Aggarwal, S. R. 2014. A survey of breakthrough therapy designations. *Nature Biotechnology* 32:323–30.

Aghamolla, C., and R. T. Thakor. 2021. IPO peer effects. *Journal of Financial Economics* 144:206–26.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. 2005. Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics* 120:701–28.

Aghion, P., R. Blundell, R. Griffith, P. Howitt, and S. Prantl. 2009. The effects of entry on incumbent innovation and productivity. *Review of Economics and Statistics* 91:20–32.

Ai, C., and E. C. Norton. 2003. Interaction terms in logit and probit models. *Economics Letters* 80:123–9.

Alder, S. 2010. Competition and innovation: Does the distance to the technology frontier matter? Working Paper, Swiss National Bank.

Amable, B., L. Demmou, and I. Ledezma. 2010. Product market regulation, innovation, and distance to frontier. *Industrial and Corporate Change* 19:117–59.

Amable, B., I. Ledezma, and S. Robin. 2016. Product market regulation, innovation, and productivity. *Research Policy* 45:2087–104.

Angelmar, R. 1985. Market structure and research intensity in high-technological-opportunity industries. *Journal of Industrial Economics* 34:69–79.

Aronson, J. K., and A. R. Green. 2020. Me-too pharmaceutical products: History, definitions, examples, and relevance to drug shortages and essential medicines lists. *British Journal of Clinical Pharmacology* 86:2114–22.

Artes, J. 2009. Long-run versus short-run decisions: R&D and market structure in Spanish firms. *Research Policy* 38:120–32.

Autor, D. H., D. Dorn, and G. H. Hanson. 2013. The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review* 103:2121–68.

Autor, D., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu. 2020. Foreign competition and domestic innovation: Evidence from US patents. *American Economic Review: Insights* 2:357–74.

Bassanini, A., and E. Ernst. 2002. Labour market regulation, industrial relations and technological regimes: A tale of comparative advantage. *Industrial and Corporate Change* 11:391–426.

Benito, P., M. E. Rochina-Barrachina, and A. Sanchis. 2017. Competition and innovation with selective exit: an inverted-U shape relationship? *Oxford Economic Papers* 69:1032–53.

Bertrand, M., and S. Mullainathan. 2003. Enjoying the quite life? Corporate governance and managerial preferences. *Journal of Political Economy* 111:1043–75.

Bhat, B., S. Karve, and D. G. Anderson. 2021. mRNA therapeutics: Beyond vaccine applications. *Trends in Molecular Medicine* 27:923–24.

Bloom, N., M. Draca, and J. Van Reenen. 2016. Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *Review of Economic Studies* 83:87–117.

Blundell, R., R. Griffith, and J. Van Reenen. 1999. Market share, market value and innovation in a panel of British manufacturing firms. *Review of Economic Studies* 66:529–54.

Boone, J., E. Brouwer, L. Filistrucchi, and H. van der Wiel. 2011. Relaxing competition through product innovation. Working Paper, Tilburg University.

Budish, E., B. N. Roin, and H. Williams. 2015. Do firms underinvest in long-term research? Evidence from cancer clinical trials. *American Economic Review* 105:2044–85.

Campbell, E. G., G. Pham-Kanter, C. Vogeli, and L. I. Iezzoni. 2013. Physician acquiescence to patient demands for brand-name drugs: results of a national survey of physicians. *JAMA Internal Medicine* 173:237–9.

Carlin, W., M. Schaffer, and P. Seabright. 2004. A minimum of rivalry: Evidence from transition economies on the importance of competition for innovation and growth. *Contributions in Economic Analysis & Policy* 3:1–43.

Chandra, A., J. Kao, K. Miller, and A. Stern. 2024. Regulatory incentives for innovation: The FDA's breakthrough therapy designation. *Review of Economics and Statistics*. Advance Access published March 18, 2024, 10.1162/rest_a_01434.

Chen, Z., Z. Liu, J. C. S. Serrato, and D. Y. Xu. 2021. Notching R&D Investment with Corporate Income Tax Cuts in China. *American Economic Review* 111:2065–100. doi:10.1257/aer.20191758.

Comanor, W. S. 1967. Market structure, product differentiation, and industrial research. *Quarterly Journal of Economics* 81:639–57.

Cornea, J. A., and C. Ornaghi. 2014. Competition & innovation: Evidence from U.S. patent and productivity data. *Journal of Industrial Economics* 62:258–85.

Crepon, B., E. Duguet, and J. Mairessec. 1998. Research, innovation and productivity: an econometric analysis at the firm level. *Economics of Innovation and New Technology* 7:115–58.

Culbertson, J. D., and W. F. Mueller. 1985. The influence of market structure on technological performance in the food-manufacturing industries. *Review of Industrial Organization* 2:40–54.

Cunningham, C., F. Ederer, and S. Ma. 2021. Killer acquisitions. *Journal of Political Economy* 129:649–702.

Cusolito, A. P., A. G.-Marin, and W. F. Maloney. 2023. Proximity to the frontier, markups, and the response of innovation to foreign competition: Evidence from matched production-innovation surveys in Chile. *AER: Insights* 5:35–54.

Czarnitzki, D., F. Etro, and K. Kraft. 2014. Endogenous market structures and innovation by leaders: An empirical test. *Economica* 81:117–39.

Darrow, J. J., J. Avorn, and A. S. Kesselheim. 2018. The FDA breakthrough-drug designation-Four years of experience. *New England Journal of Medicine* 378:1444–53.

De Loecker, J., and P. K. Goldberg. 2014. Firm performance in a global market. *Annual Review of Economics* 6:201–27.

Donelson, D., J. A. Garfinkel, and S. Roudini. 2024. Regulatory policy enforcement and corporate performance. Working Paper.

Ethiraj, S., and Y. M. Zhou. 2019. Fight or flight? Market positions, submarket interdependencies, and strategic responses to entry threats. *Strategic Management Journal* 40:1545–69.

Frésard, L., and P. Valta. 2016. How does corporate investment respond to increased entry threat? *Review of Corporate Finance Studies* 5:1–35.

Geroski, P. A. 1991. Entry and the rate of innovation. *Economics of Innovation and New Technology* 1:203–14.

Geroski, P. A., and R. Pomroy. 1990. Innovation and the evolution of market structure. *Journal of Industrial Economics* 38:299–314.

Gong, R. K., and R. Xu. 2017. Does import competition induce R&D reallocation? Evidence from the U.S. Working Paper, IMF.

Goolsbee, A., and C. Syverson. 2008. How do incumbents respond to the threat of entry? Evidence from the major airlines. *Quarterly Journal of Economics* 123:1611–33.

Guedj, I., and D. Scharfstein. 2004. Organizational scope and investment: Evidence from the drug development strategies of biopharmaceutical firms. Working Paper.

Hammoudeh, M., and A. Nain. 2019. Seeking efficiency or price gouging? Evidence from pharmaceutical mergers. Evidence from pharmaceutical mergers. *Journal of Corporate Finance* 87:102623.

Hashmi, A. R. 2013. Competition and innovation: The inverted-U relationship revisited. Review of Economics and Statistics 95:1653–68.

Hay, M, D. W. Thomas, J. L. Craighead, C. Economides, and J. Rosenthal. 2014. Clinical development success rates for investigational drugs. Nature Biotechnology 32:40–51.

Hermosilla, M. 2021. Rushed innovation: Evidence from drug licensing. *Management Science* 67:257–78.

———. 2024. Regulating ethical experimentation: Impacts of the breakthrough therapy designation on drug R&D. *Journal of Health Economics* 94:102855.

Hoberg, G. and Phillips, G., 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy* 124:1423–65.

Hoberg, G., and G. M. Phillips. Forthcoming. Scope, scale and competition: The 21st century firm. *Journal of Finance*.

Hoberg, G., Y. Li, and G. M. Phillips. 2021. US-China innovation competition. Working Paper, Tuck School of Business.

Hoffmann, D., S. Van Dalsem, and F. S. David. 2019. Stock price effects of breakthrough therapy designation. *Nature Reviews Drug Discovery* 18:165–6.

Hombert, J., and A. Matray. 2018. Can innovation help US manufacturing firms escape import competition from China? *Journal of Finance* 73:2003–39.

Hwang, T. J., J. M. Franklin, C. T. Chen, J. C. Lauffenburger, B. Gyawali, A. S. Kesselheim, and J. J. Darrow. 2018. Efficacy, safety, and regulatory approval of Food and Drug Administration-designated breakthrough and nonbreakthrough cancer medicines. *Journal of Clinical Oncology* 36:1805–12.

Kalmenovitz, J., M. Lowry, and K. Volkova. Forthcoming. Regulatory fragmentation. *Journal of Finance*.

Kesselheim, A. S., S. Woloshin, W. Eddings, J. M. Franklin, K. M. Ross, and L. M. Schwartz. 2016. Physicians' knowledge about FDA approval standards and perceptions of the "breakthrough therapy" designation. *JAMA* 315:1516–18.

Khanna, N., and S. Tice. 2000. Strategic responses of incumbents to new entry: The effect of ownership structure, capital structure, and focus. *Review of Financial Studies* 13:749–79.

———. 2001. The bright side of internal capital markets. *Journal of Finance* 56:1489–528.

Krishnamurti, T., S. Woloshin, L. M. Schwartz, and B. Fischhoff. 2015. A randomized trial testing US Food and Drug Administration "breakthrough" language. *JAMA Internal Medicine* 175:1856–58.

Krieger, J. L. 2021. Trials and terminations: Learning from competitors' R&D failures. *Management Science* 67:5525–48.

Krieger, J., X. Li, and R. T. Thakor. 2020. Find and replace: R&D investment following the erosion of existing products. Working Paper.

Kwoka, J., and B. Batkeyev. 2019. Strategic responses to competitive threats: Airlines in action. *Review of Industrial Organization* 54:83–109.

Lam, B. P., T. Jeffers, Z. Younoszai, Y. Fazel, and Z. M. Younossi. 2015. The changing landscape of hepatitis C virus therapy: focus on interferon-free treatment. *Therapeutic Advances in Gastroenterology* 8:298–312.

Lee, C.-Y. 2009. Competition favors the prepared firm: Firms' R&D responses to competitive market pressure. *Research Policy* 38:861–70.

Levin, S. G., S. L. Levin, J. B. Meisel. 1985. Intermarket Differences in the Early Diffusion of an Innovation. *Southern Economic Journal* 51:672–80.

Li, X., A. W. Lo, and R. T. Thakor. 2021. Paying off the competition: Market power and innovation incentives. Working Paper, University of South Carolina.

Li, X., T. Liu, and L. A. Taylor. 2023. Common ownership and innovation efficiency. *Journal of Financial Economics* 147:475–97.

Lichtenberg, F. R., and T. J. Philipson. 2002. The dual effects of intellectual property regulations: Within- and between-patent competition in the U.S. pharmaceuticals industry. *Journal of Law and Economics* 45:643–72.

Link, A. N., and J. Lunn. 1984. Concentration and the returns to R&D. *Review of Industrial Organization* 1:232–5.

Lo, A. W., and R. T. Thakor. 2022. Financing biomedical innovation. *Annual Review of Financial Economics* 14:231–70.

Long, J. S. 1997. *Regression models for categorical and limited dependent variables*, vol. 7. New York: Sage.

Lunn, J. 1986. An empirical analysis of process and product patenting: A simultaneous equation framework. *Journal of Industrial Economics* 34:319–30.

Mansfield, E. 1981. Composition of R&D expenditures: Relationship to size of firm, concentration, and innovative output. *Review of Economics and Statistics* 63:610–5.

Moser, P. 2012. Innovation without patents: Evidence from World's Fairs. *Journal of Law and Economics* 55:43–74.

Nickell, S. J. 1996. Competition and corporate performance. *Journal of Political Economy* 104:724–46.

Parise, G. 2018. Threat of entry and debt maturity: Evidence from airlines. *Journal of Financial Economics* 127:226–47.

Peneder, M., and M. Worter. 2011. Competition, technological opportunities, and entrepreneurship: Estimating a system of simultaneous equations. *Journal of Evolutionary Economics* 24:653–87.

Phillips, G. M., and A. Zhdanov. 2013. R&D and the incentives from merger and acquisition activity. *Review of Financial Studies* 26:34–78.

Romer, P. M. 1990. Endogenous technological change. *Journal of Political Economy* 98:S71–S102.

Santos, C. D. 2010. Competition, product and process innovation: an empirical analysis. Working Paper.

Scherer, F. M. 1965. Firm size, market structure, opportunity, and the output of patented inventions. *American Economic Review* 55:1097–125.

———. 1967. Market structure and the employment of scientists and engineers. *American Economic Review* 57:524–31.

Schmidt, K. M. 1997. Managerial incentives and product market competition. *Review of Economic Studies* 64:191–213.

Schumpeter, J. A. 1943. *Capitalism, socialism, and democracy*. New York: Harper.

Schwartz, L. M., and S. Woloshin. 2019. Medical marketing in the United States, 1997-2016. *JAMA* 321:80–96.

Senior, M. 2013. Drugs with breakthrough status charm investors. *Nature Biotechnology* 31:945–48.

Sherman, R. E., J. Li, S. Shapley, M. Robb, and J. Woodcock. 2013. Expediting drug development—the FDA's new "breakthrough therapy" designation. *New England Journal of Medicine* 369:1877–80.

Sukhatme, N. U., and J. N. L. Cramer. 2019. Who cares about patents? Cross-industry differences in the marginal value of patent term. *American Law and Economics Review* 21:1–45.

Tang, J. 2006. Competition and innovation behaviour. Research Policy 35:68–82.

Tenn, S., and B. W. Wendling. 2014. Entry threats and pricing in the generic drug industry. *Review of Economics and Statistics* 96:214–28.

Thakor, R. T., and A. W. Lo. 2019. Competition and R&D financing: Evidence from the biopharmaceutical industry. *Journal of Financial and Quantitative Analysis* 57:1885–928.

Tingvall, P. G., and A. Poldahl. 2006. Is there really an inverted U-shaped relation between competition and R&D? *Economics of Innovation and New Technology* 15:101–18.

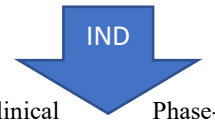
Tomy, R. E. 2019. Threat of entry and the use of discretion in banks' financial reporting. *Journal of Accounting and Economics* 67:1–35.

Van Norman, G. A. 2016. Drugs, devices, and the FDA: part 1: an overview of approval processes for drugs. *JACC: Basic to Translational Science* 1:170–9.

Wang, B., and A. S. Kesselheim. 2013. The role of direct-to-consumer pharmaceutical advertising in patient consumerism. *AMA Journal of Ethics* 15:960–65.

Wen, W., and F. Zhu. 2019. Threat of platform-owner entry and complementor responses: Evidence from the mobile app market. *Strategic Management Journal* 40:1336–67.

Zoulim, F., T. J. Liang, A. L. Gerbes, A. Aghemo, S. Deuffic-Burban, G. Dusheiko, M. W. Fried, S. Pol, J. K. Rockstroh, N. A. Terrault, and S. Wiktor. 2015. Hepatitis C virus treatment in the real world: optimising treatment and access to therapies. *Gut* 64:1824–33.



Development stage	Discovery	Preclinical	Phase-I	Phase-II	Phase-III	FDA decision
EAP application			*BTD*		*Fast track*	*Accelerated approval & priority review*
Purpose	Identify promising molecules	Animal and lab testing	Drug safety test in humans	Drug safety & efficacy tests in humans	Large-scale safety & efficacy tests in humans	
# of participants			10 to 50	50 to 200	200 to 3,000	FDA reviews evidence from clinical trials and approves or denies the NDA application
Development time (yr)	4 to 8		< 1	1 to 3	2 to 4	
Cost (in $ mil.)	1 to 7		1 to 5	7 to 20	10 to 75	
% move to next stage	30		70	33	50	
% approval likelihood	<5		10	15	50	

Figure 1. An illustrative description of the drug development process in the United States
For each stage of development, the following information is provided. *EAP application* identifies the recommended development stages for applying to any of the FDA's expedited approval programs. *Purpose* identifies the objective of each development stage. *# of participants* displays the average number of human volunteers in a given clinical stage. *Development time* reports the average number of years a drug project spends in a given stage before moving on to the next one. *Cost* provides the average cost (in $millions) associated with a given stage. *% move to next stage* reports the average percentage of drug projects in a given stage that eventually move on to the next one. *% approval likelihood* shows the average probability that a drug project in a given stage eventually receives FDA approval. The two arrows in the first row indicate the timing for IND and NDA applications. IND is an abbreviation for investigational new drug application, and NDA is an abbreviation for new drug application.

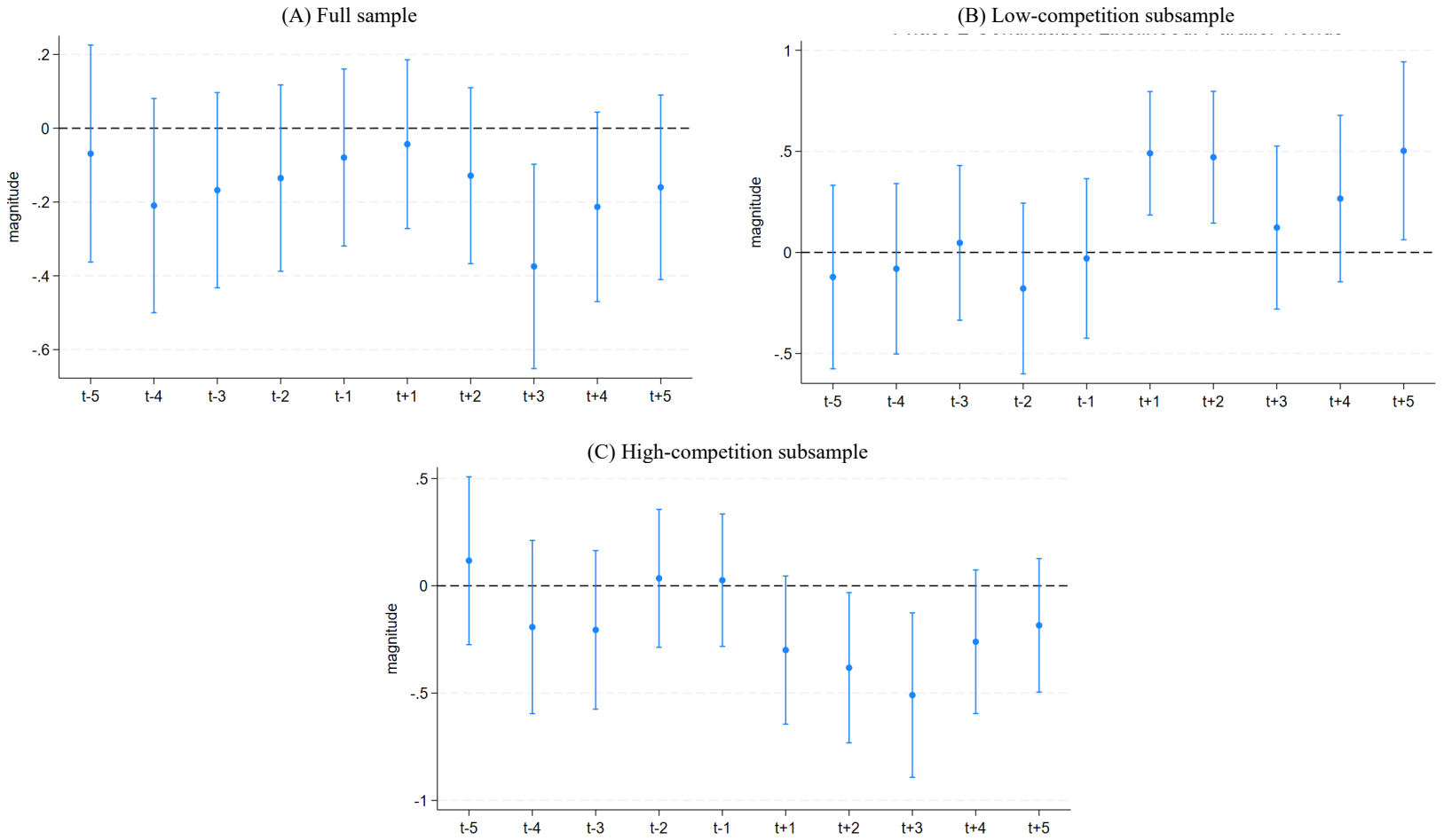


Figure 2. Coefficients from a Cox proportional hazards model that estimates the graduation (to phase-III) rates of rival phase-II projects relative to control projects, in the 5 years before and 5 after, BTD entry into a therapeutic market

The success event, *Graduation*, is an indicator equal to one in the quarter that a project graduates to phase-III, and equal to zero in all quarters where it remains in phase-II. The analysis time is the number of quarters since the start of phase-II. The analysis sample is summarized in Table 5. The plotted coefficients are interaction variables between an indicator, ever-BTD shocked, which equals one if a phase-II project ever experiences BTD entry, with annual event time indicators for each of the 5 years before and after BTD entry. The bar caps cover the 95% confidence intervals for each coefficient. The Cox proportional hazards model is stratified by therapeutic market, includes calendar quarter fixed effects, and clusters standard errors by drug project. The analysis sample in Figure 2A is the full sample of phase-II projects. The sample in panel B (panel C) includes phase-II projects in markets with low (high) competition, that is, markets with competition levels below (above) the median competition level in the full phase-II sample.

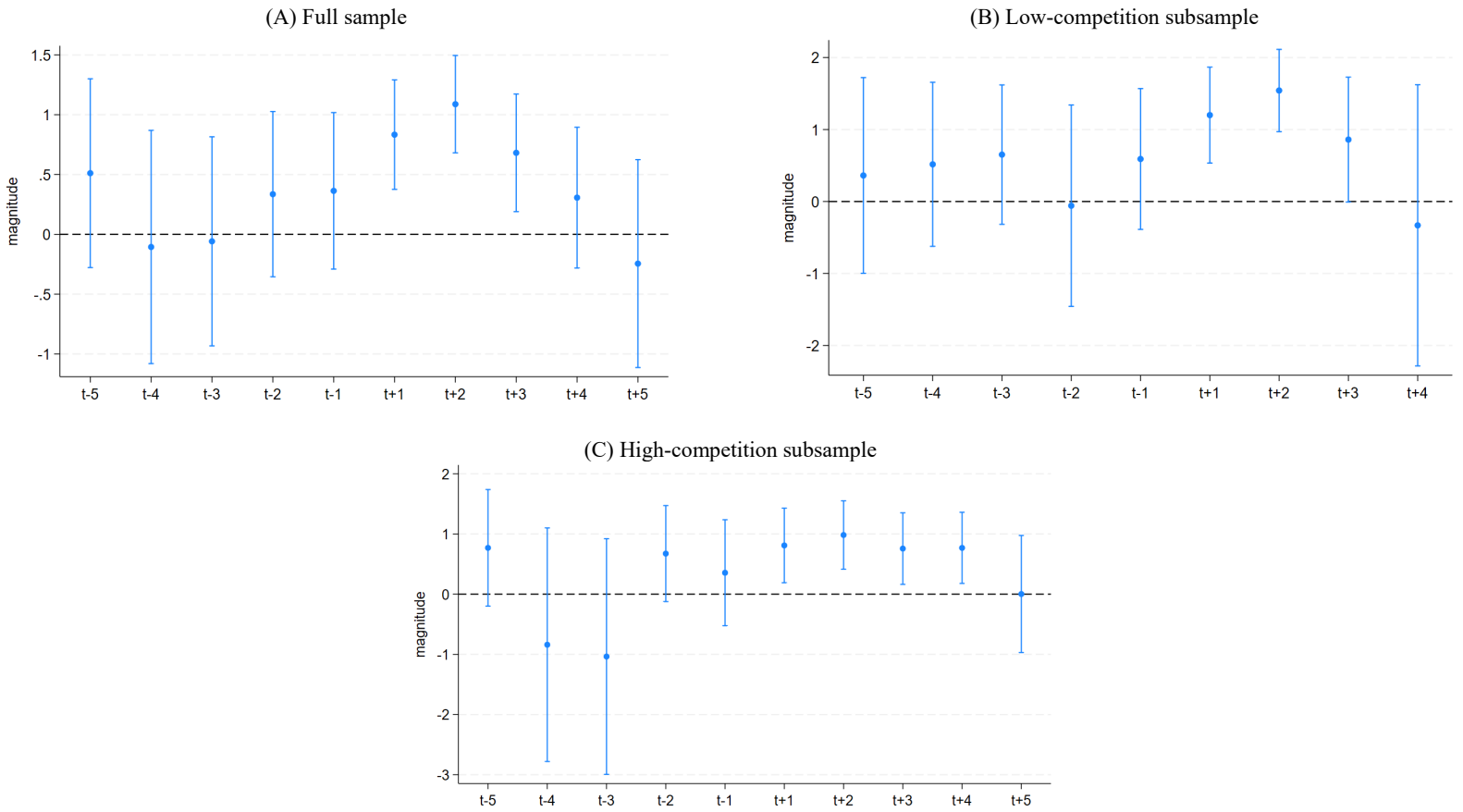


Figure 3: Coefficients from a Cox proportional hazards model that estimates the graduation (to phase-III) rates of rival SMST phase-II projects relative to control projects, in the 5 years before and 5 after, BTD entry into a therapeutic market

The success event, *Graduation*, is an indicator equal to one in the quarter that a project graduates to phase-III, and equal to zero in all quarters where it remains in phase-II. The analysis time is the number of quarters since the start of phase-II. The analysis sample is summarized in Table 5. The plotted coefficients are interaction variables between an indicator, ever-SMST with annual event time indicators for each of the 5 years before and after BTD entry. Ever-SMST is an indicator that equals one if a rival's phase-II project ever experiences the entry of a BTD drug in its market that uses the same technology (i.e., the rival's phase-II project shares at least one target action with the BTD drug). The bar caps cover the 95% confidence intervals for each coefficient. The Cox proportional hazards model is stratified by therapeutic market, includes calendar quarter fixed effects, and clusters standard errors by drug project. The analysis sample in Figure 3A is the full sample of phase-II projects. The sample in panel B (panel C) includes phase-II projects in markets with low (high) competition, that is, markets with competition levels below (above) the median competition level in the full phase-II sample.

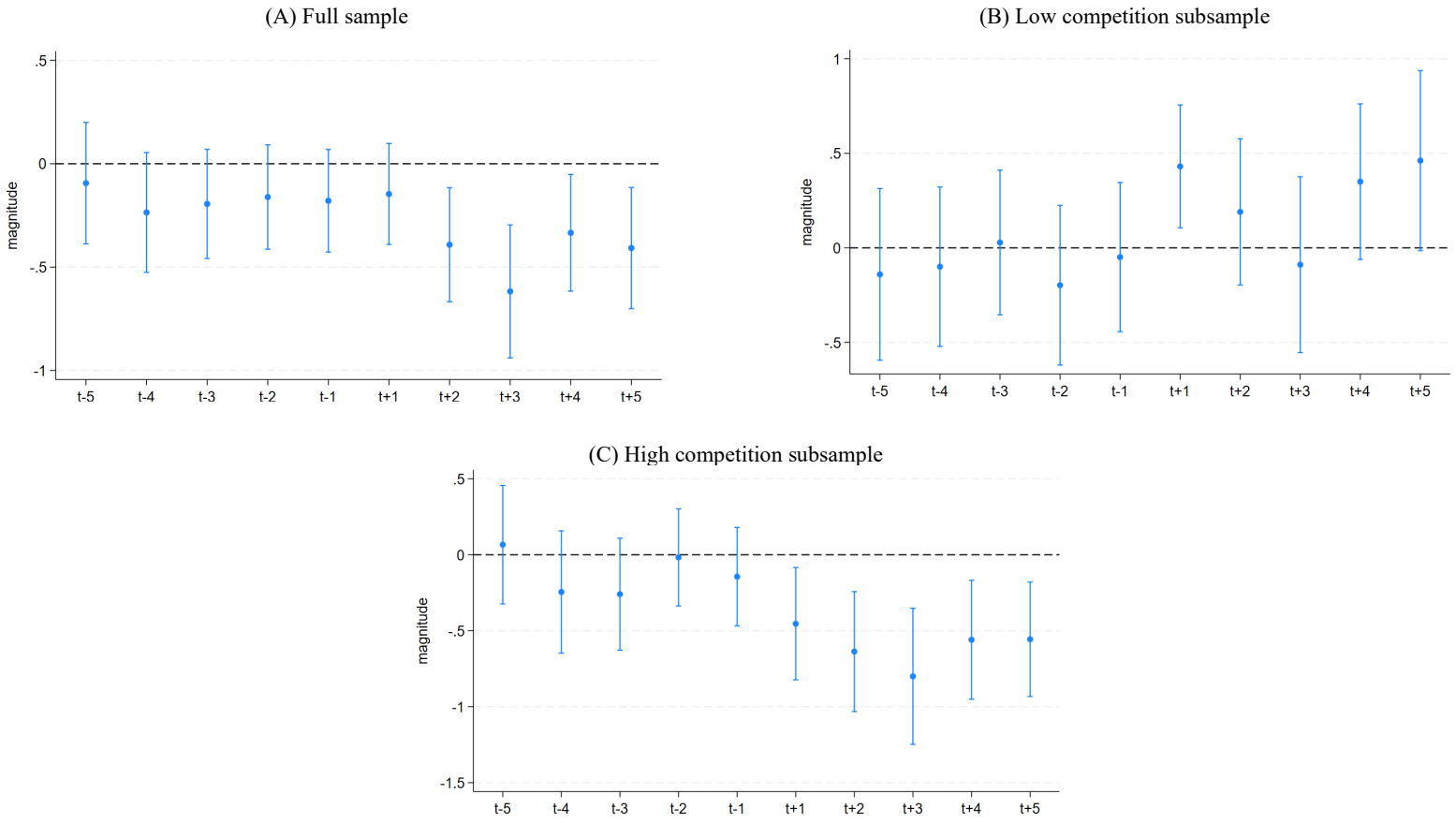


Figure 4: Coefficients from a Cox proportional hazards model that estimates the graduation (to phase-III) rates of rival SM [only] phase-II projects relative to control projects, in the 5 years before and 5 after, BTD entry into a therapeutic market

The success event, *Graduation*, is an indicator equal to one in the quarter that a project graduates to phase-III, and equal to zero in all quarters where it remains in phase-II. The analysis time is the number of quarters since the start of phase-II. The analysis sample is summarized in Table 5. The plotted coefficients are interaction variables between an indicator, ever-SM with annual event time indicators for each of the 5 years before and after BTD entry. Ever-SM is an indicator that equals one if a rival's phase-II project ever experiences the entry of a BTD drug in its market that uses a different technology (i.e., the rival's phase-II project uses different target actions than those used by the BTD drug). The bar caps cover the 95% confidence intervals for each coefficient. The Cox proportional hazards model is stratified by therapeutic market, includes calendar quarter fixed effects, and clusters standard errors by drug project. The analysis sample in Figure 4A is the full sample of phase-II projects. The sample in panel B (panel C) includes phase-II projects in markets with low (high) competition, that is, markets with competition levels below (above) the median competition level in the full phase-II sample

Table 1. Sampling of literature on competition-innovation relationship and the potential influence of aggregation and distance-to-frontier measurement problems

Papers selected (nonrandomly) from output of Google Scholar searches on "Competition, Innovation, Inverted-U, Incumbent Innovation." Selected papers vary in conclusions on shape of competition-innovation relationship. Chose three periods: pre-inverted-U work; period around workhorse Aghion et al. (2005); approximate 10-year window finishing by 2023. Papers listed in footnotes. "?"s indicate no information provided on industry-count. In some cases, the number of industries is replaced by the number of product markets, per the paper's discussion.

[a] See Scherer (1965, 1967), Comanor (1967), Mansfield (1981), Scot (1984), Link and Lunn (1984), Culbertson and Muller (1985), Levin et al. (1985), Anglemar (1985), Lunn (1986), and Geroski (1990, 1991).
[b] See Crepon et al. (1998), Blundell et al. (1999), Bassanini and Ernst (2002), Carlin et al. (2004), Aghion et al. (2005), Tang (2006), Tingvall and Poldahl (2006), Aghion et al. (2009), Artes (2009), Lee (2009), Amable et al. (2010), Alder (2010), Santos (2010), Boone et al. (2011), and Peneder and Worter (2011).
[c] See Hashmi (2013), Autor et al. (2020), Xu and Gong (2017), Cusolito et al. (2023), Correa and Ornaghi (2014), Benito et al. (2017), Czarnitzki et al. (2014), and Amable et al. (2016).

Early work = 11 papers. End by 1991.[a] Two papers have two different shapes in subsamples.

Shape of relationship	# papers with shape	# countries (across papers)	# industries (across papers)	# papers meas. distance to frontier
U – shaped	1	1	14	0
Inverted – U	1	1	56	0
Positive	2	1, 6	21, 6	1
Negative	4	1, 1, 6, 1	1, 1, 6, 191	1
Zero	5	1, 1, 1, 1, 1	12, 259, 1, 191, 73	0

More recent = 15 papers (7 survey based). Through 2012.[b] Two papers have two different shapes in subsamples.

Shape of relationship	# papers with shape	# countries (across papers)	# industries (across papers)	# papers meas. distance to frontier
U – shaped	0			
Inverted – U	7	24, 1, 1, 1, 6, 40, 1	5+, 17, 11, 60, ?, ?, 28	3
Positive	5	1, 18, 1, 17, 1	5+, 5+, 21, 15, 160	2
Negative	5	1, 24, 1, 1, 1	1, 5+, 21, 18, ?	2
Zero	0			

Most recent empirical (post-2012).[c] N = 8 papers. 1 paper shows different shapes in subsamples.

Shape of relationship	# papers with shape	# countries (across papers)	# industries (across papers)	# papers meas. distance to frontier
U – shaped	0			
Inverted – U	0			
Positive	4	1, 1, 1,1	10, 223, 80, 14	2
Negative	5	1, 1, 1, 1, 17	116, 11, 5+, 10, 13	2
Zero	0			

Table 2. Competition-innovation relationship and the influence of firm scope

The tests in this table examine the effect of Chinese import penetration of U.S. industries on firm-level innovation. The sample consists of annual information on 4,230 firms in 120 4-digit SIC manufacturing industries over the period from 1991 to 2011. The observation level of the sample is firm-year. Data on Chinese import penetration is obtained from Autor, Dorn and Hanson (2013). For each industry-year, we obtain the ratio of U.S. imports, as well as the same ratio for a sample of comparison countries' summed imports, from China to the same industry's U.S. market volume in 1991. The results reported in this table are from the second stage of a 2SLS regression. We follow a similar identification strategy to that of Autor, Dorn, and Hanson (2013). We instrument U.S. Chinese imports (and its square) with the Chinese imports for a sample of comparison countries' (and its square). All regressors and instrumental variables are lagged by 1 year.
The tests below partition the sample by firm scope. Firm scope is a measure for the breadth of product markets that a firm actively operates in. Scope data have been obtained from Hoberg and Phillips (2023). The first two columns of panel A use the full sample of firm-years. Columns 3 and 4 (5 and 6) of panel A use the sample of firm-years that fall below (above) the median of firm scope. In columns 1 and 2 of panel B (panel C), the tests are based on the subsample of firm-years that are in the bottom tercile (quartile). In columns 3 and 4 of panel B (panel C), the tests are based on subsample of firm-years in the top tercile (quartile) of firm scope.
The dependent variables in the tests below are indicated in the column headings and are either R&D expense divided by total assets (R&D/AT) or the number of citation-weighted patents. R&D and total assets are obtained from Compustat Annual files. Patents and citations are obtained from Kogan et al. (2017) (KPSS) data.
All tests below include the following fixed effects: industry, year, and number of segments (obtained from Compustat segment data). Standard errors are clustered by firm. *t*-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. Scope sorted into medians

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample		Low scope (below median)		High scope (above median)	
Dependent var:	R&D/AT	CiteW Patent	R&D/AT	CiteW Patent	R&D/AT	CiteW Patent
U.S. China import	0.006**	0.121***	0.009*	0.137**	0.001	0.238
	(2.063)	(2.608)	(1.935)	(2.410)	(0.919)	(1.295)
U.S. China import²	-0.0003**	-0.001**	-0.001*	-0.001*	-0.000	-0.001
	(-2.185)	(-2.425)	(-1.914)	(-1.690)	(-1.205)	(-0.866)
Observations	38,489	33,874	21,545	19,770	16,937	14,097
R-squared	.000	.000	.000	.001	.000	.003

B. Scope sorted into terciles (only top and bottom terciles included and the middle tercile is excluded)

	(1)	(2)	(3)	(4)
	Low scope (low tercile)		High scope (top tercile)	
Dependent var:	R&D/AT	CiteW patent	R&D/AT	CiteW patent
U.S. China import	0.010*	0.221***	0.000	0.133
	(1.806)	(3.696)	(0.238)	(0.548)
U.S. China import²	-0.001*	-0.001**	-0.000	-0.002
	(-1.874)	(-2.251)	(-0.753)	(-1.183)
Observations	14,985	13,629	11,608	9,077
R-squared	.000	.001	.001	.000

C. Scope sorted into quartiles (only top and bottom quartiles reported and the middle quartiles are excluded)

	(1)	(2)	(3)	(4)
	Low scope (low quartile)		High scope (top quartile)	
Dependent var:	R&D/AT	CiteW Patent	R&D/AT	CiteW Patent
U.S. China import	0.013*	0.211***	0.000	0.196
	(1.649)	(3.523)	(0.170)	(0.679)
U.S. China import²	-0.001*	-0.001**	-0.000	-0.003
	(-1.667)	(-2.223)	(-0.805)	(-1.465)
Observations	11,535	10,456	9,539	7,115
R-squared	.000	.001	.000	.001

Table 3. Announcement returns of BTD firms, rivals, and control firms around BTD events

This table presents OLS regressions of cumulative abnormal returns (CARs) around BTD announcements. The sample includes BTD firms, rival firms and control firms. CARs are based on a market model with parameters estimated during trading days [−271, −21], relative to the BTD grant announcement date. The dependent variable (CAR) is actual return minus market-model-predicted return, cumulated over the 3 trading days [-1, +1] surrounding the BTD award announcement. CARs are winsorized at the 1% and 99% levels. BTD firms are those that received the BTD award on the event date. Control firms are firms with products that do not fall in the ICD-10 market that experienced BTD entry on the event date.

BTD rival is an indicator equal to one for firms that have any drug project that targets an ICD-10 market and that experienced BTD entry on the event date. SMST, an abbreviation for same market same technology, is an indicator equal to one for rival firms that were shocked by BTD entry to a market where at least one of the rival's drug projects uses a technology (i.e., target action) that is the same technology used by the BTD-awarded drug. SM is an indicator equal to one for rival firms shocked by BTD entry in a product market where that rival's projects do not share any technological similarities with the BTD-awarded project. Column 1 and 2 present regression results for the full sample. Column 3 presents regression results for the sample of rival firms only. In column 3, the sample drops BTD firms completely from the quarter in which they received the BTD designation and until the end of the sample (this step helps avoid any confounding effects that may arise when subsequent BTD awards use similar technology as that used by the former BTD). In total, the tests below are based on the announcement returns of 957 unique firms around 343 BTD announcements. Standard errors are clustered by firm. *t*-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

	Full sample	Full sample	Rivals-only sample
	(1)	(2)	(3)
BTD firm	0.026***	0.026***	
	(4.140)	(4.150)	
BTD rival	-0.001**		
	(-2.186)		
SMST rival		0.001	0.011**
		(0.360)	(2.115)
SM rival		-0.002*	
		(-1.912)	
Observations	172,589	172,589	12,385
R-squared	.080	.080	.106
Firm FE	Yes	Yes	No
Event-day FE	Yes	Yes	Yes

Table 4. BTD shocks and innovation at pharma firms: Firm-level aggregation concerns within pharma

The tests in this table use OLS regressions to examine firm-level innovation following BTD events. BTD Firm is an indicator equal to one for firms that received a BTD award in one of the previous 4 quarters. *BTD rival* is an indicator equal to one for firms developing operating in markets that experienced BTD entry in one of the last 4 quarters. SMST is an indicator equal to one for rival firms that were shocked by BTD entry in the previous four quarters in a market where at least one of the rival's drug projects uses a technology (i.e., target action) that is the same technology used by the BTD-awarded drug. *SM* is an indicator equal to one for rival firms shocked by BTD entry in the previous 4 quarters in a product market where that rival's projects do not share any technological similarities with the BTD-awarded project. In columns 1–3, the dependent variable is the citation weighted number of patents; in columns 4–6, the dependent variable is a dummy equal to 1 if the firm had issued a patent in the corresponding quarter; and in columns 7 and 8, the dependent variable is equal to the quarterly R&D expense divided by total assets. The full sample is included where the column heading indicates "full sample," whereas only the sample of rivals is included where the column heading indicates "rivals only." Standard errors are clustered by firm. *t*-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

	Patent dummy			Citation-weighted patents			R&D/TA		
	Full sample		Rivals only	Full sample		Rivals only	Full sample		Rivals only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BTD firm	-0.036*	-0.031		-10.615	-6.865		-0.012	-0.013	
	(-1.816)	(-1.569)		(-0.267)	(-0.176)		(-0.693)	(-0.746)	
BTD rival	0.002			4.192			-0.012		
	(0.407)			(1.287)			(-1.458)		
SMST rival		-0.045***	-0.023		-35.906**	-11.687		0.004	0.001
		(-3.197)	(-1.465)		(-1.987)	(-1.148)		(0.327)	(0.049)
SM rival		0.004			5.667			-0.010	
		(0.675)			(1.621)			(-1.117)	
Observations	35,951	35,951	10,431	35,951	35,951	10,431	25,901	25,901	8,669
R-squared	.493	.493	.532	.644	.645	.801	.194	.194	.194
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. Summary statistics on the phase-II development sample

This table presents summary statistics for phase-II projects, therapeutic markets, and developer firms appearing in the phase-II development sample. Phase-II projects owned by BTD awarded firms are dropped from the sample if they target the same market in which the BTD firm was awarded. The observation level in the sample is project-quarter and is displayed in the first row of each panel for each corresponding sample. In both panels below, the variables *# of projects*, *# of markets*, *# of firms* display the unique number of phase-II projects, number of therapeutic markets and number of firms developing phase-II projects in each corresponding sample, respectively. *% graduated* reports the percentage of all phase-II projects that advance to phase-III in the corresponding sample. Competition displays the average number of competing rival projects in the same market. *Mkt exp %* is the average exposure of a firm in a market and is calculated as the number of projects owned by a firm in that market divided by the total number of projects owned by a firm. In both panels below, columns titled "All" include all phase two projects in the corresponding example. Whereas columns titled "Low comp" ("Hi comp") use the subsample of phase two projects in markets with low (High) competition, that is, markets with competition levels below (above) the median level of competition in the full sample.
In panel A, the first three column are based on the full sample, columns 4–6 are based on the subsample of rival phase-II projects that have ever experienced a BTD shock and columns 7 and 8 are based on the subsample of control phase-II projects that have never experienced BTD entry. In panel B, the sample focuses only on rival phase-II projects. The first 3 columns display the corresponding statistics for rival SM phase-II projects that experience BTD entry but use technology that is different from that used by the BTD-awarded drug. In columns 4–6 of panel B, statistics are displayed for rival SMST phase-II projects that experience BTD entry and use the same technology that was used by the drug that was awarded a BTD in the same market.

A. Summary statistics on rivals', and control firms', phase-II projects

		All projects		Projects ever shocked by BTD			Projects never shocked by BTD		
Subsample	All	Low comp	Hi comp	All	Low comp	Hi comp	All	Low comp	Hi comp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
N	195,736	85,846	109,890	97,900	20,974	76,926	97,836	32,964	64,872
# of projects	12,038	5,838	6,200	5,167	1,197	3,970	6,871	4,641	2,230
# of markets	992	959	104	185	168	55	807	791	49
# of firms	2,319	1698	1540	1,319	906	1116	1,000	792	424
% graduated	12.97	15.98	10.01	7.57	14.61	5.34	16.99	16.33	18.38
Competition	4.34	3.11	5.53	4.97	3.51	5.566	3.61	2.92	5.44
Market exp %	12.19	12.08	12.31	11.17	10.36	11.51	13.38	12.88	14.73

B. Summary statistics for rivals' phase-II projects conditional on the type of rival

	Rival SM projects			Rival SMST projects		
Subsample	All	Low comp	Hi comp	All	Low comp	Hi comp
	(1)	(2)	(3)	(4)	(5)	(6)
N	55,247	11,531	43,716	5,816	1,195	4,621
# of projects	4,730	1,092	3,638	526	114	412
# of markets	183	153	55	86	51	41
# of firms	1,254	582	991	270	81	221
% graduated	6.79	14.11	4.58	15.26	25.83	12.36
Competition	5.21	3.63	5.68	5.22	3.52	5.68
Market exp %	10.78	11.19	10.65	13.11	8.28	14.45

Table 6. Phase-II development and BTD shocks

The tests in this table examine the likelihood of phase-II development following BTD shocks. The results displayed below are from the main Cox Proportional Hazards with estimates are stratified by market and the analysis time is equal to the number of quarters since the start of phase-II trials. The success event, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. The analysis sample is summarized in Table 5. Competition is calculated each quarter as the natural logarithm of the total number of drug projects in a therapeutic market. In both panels below, the full sample of phase-II projects is used in columns 1 and 2, and in columns 3 and 4, the full sample is partitioned by the level of competition; projects in markets below (above) the median level of competition are used in column 3 (column 4). Whereas the samples used in columns 5–12 are partitioned by market exposure. Market exposure is calculated by dividing the number of a firm's projects that target the focal drug project's market by the total number of projects owned by the same firm, in each quarter. The results displayed in columns 5–8 (columns 9–12) are based on the subsample of projects that fall below (above) the sample's median level of market exposure. In addition, columns 7 and 11 (columns 8 and 12) restrict the corresponding sample to projects in markets with competition levels below (above) the median level of competition in the full sample.

In panel A, the variable *BTD shock* is an indicator equal to one for all phase-II projects that reside in a market that had experienced BTD entry, and equal to zero otherwise. In panel B, the variable SM is an indicator equal to one if the focal project targets a market that had experienced BTD entry and but uses a different technology, than that used by any of the drugs that were awarded a BTD in that market. SMST is an indicator equal to one if the focal project had experienced BTD entry into its market and uses at least one target action (i.e., technology) that is also used by any of the drugs that were awarded a BTD in the same market. Standard errors are clustered by drug-project z-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. Product-level tests of BTD shocks and phase-II development

	Full sample (any exposure)				***Low market exposure***				***High market exposure***			
	Any cmp		Lo cmp	Hi cmp	Any cmp		Lo cmp	Hi cmp	Any cmp		Lo cmp	Hi cmp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BTD shock	0.013	1.173***	0.426***	-0.265***	0.099	0.803**	0.315**	-0.042	-0.087	1.408***	0.558***	-0.517***
	(0.181)	(5.498)	(4.101)	(-2.718)	(1.026)	(2.543)	(2.254)	(-0.314)	(-0.837)	(4.691)	(3.484)	(-3.602)
*BTD shock*Comp*		-0.245***				-0.149**				-0.316***		
		(-5.545)				(-2.244)				(-5.159)		
Competition		0.005				0.004				-0.002		
		(0.218)				(0.119)				(-0.060)		
Observations	195,736	195,736	97,900	97,836	97,868	97,868	51,763	46,105	97,868	97,868	46,137	51,731

B. Product-level tests of BTD shocks and phase-II development conditional on the type of rival

	Full sample (any exposure)				***Low market exposure***				***High market exposure***			
	Any cmp		Lo cmp	Hi cmp	Any cmp		Lo cmp	Hi cmp	Any cmp		Lo cmp	Hi cmp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SMST	0.621***	1.238***	0.860***	0.470***	0.517***	0.382	0.500*	0.491**	0.709***	1.869***	1.248***	0.459**
	(5.132)	(2.979)	(4.496)	(2.952)	(2.857)	(0.474)	(1.677)	(2.076)	(4.311)	(4.125)	(4.909)	(2.079)
SM	-0.101	1.243***	0.363***	-0.431***	0.024	0.923***	0.288**	-0.153	-0.245**	1.432***	0.462***	-0.751***
	(-1.348)	(5.508)	(3.332)	(-4.112)	(0.238)	(2.838)	(1.977)	(-1.096)	(-2.185)	(4.435)	(2.755)	(-4.768)
*SMST*Competition*		-0.127				0.027				-0.235**		
		(-1.512)				(0.165)				(-2.558)		
*SM*Competition*		-0.286***				-0.191***				-0.358***		
		(-6.088)				(-2.783)				(-5.396)		
Competition		0.004				0.003				-0.002		
		(0.198)				(0.101)				(-0.061)		
Observations	195,736	195,736	97,900	97,836	97,868	97,868	51,763	46,105	97,868	97,868	46,137	51,731

Table 7. Phase-II development around BTD shocks in ex ante leveled markets

The tests in this table examine the effect of BTD shocks on the development likelihood of phase-II projects conditional on the ex ante levelness of the market. The table presents coefficients from the main Cox Proportional Hazards specification, which stratifies the sample by market and clusters standard errors by drug project. The model's success event, Graduation, is an indicator equal to one in the quarter that a project graduates to phase-III, and equal to zero in all quarters where it remains in phase-II. The analysis time is the number of quarters since the start of phase-II development. The analysis sample includes phase-II projects in ex ante level markets where none of the competing firms own an approved-for-sale product (i.e., no approved products are on the market). Competition is calculated each quarter as the natural logarithm of the total number of drug projects in a therapeutic market. In both panels below, the full sample of phase-II projects is used in columns 1 and 2, and in columns 3 and 4, the full sample is partitioned by the level of competition; projects in markets below (above) the median level of competition are used in column 3 (column 4).
In panel A, the variable *BTD shock* is an indicator equal to one for all phase-II projects that reside in a market that had experienced BTD entry, and equal to zero otherwise. In panel B, the variable SM is an indicator equal to one if the focal project targets a market that had experienced BTD entry and but uses a different technology, than that used by any of the drugs that were awarded a BTD in that market. SMST is an indicator equal to one if the focal project had experienced BTD entry into its market and uses at least one target action (i.e., technology) that is also used by any of the drugs that were awarded a BTD in the same market. Standard errors are clustered by drug-project z-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

	Full sample		Market competition	
			Low	High
	(1)	(2)	(3)	(4)
A. Ex ante leveled: Markets with no approved-for-sale products				
	(1)	(2)	(3)	(4)
BTD shock	0.446**	1.405***	1.091***	-2.210**
	(2.197)	(3.542)	(5.279)	(-2.184)
*BTD shock*Competition*		-0.225**		
		(-2.180)		
Observations	24,884	24,884	20,693	4,191
B. Ex ante leveled: Markets with no approved-for-sale products conditional on rival type				
	(1)	(2)	(3)	(4)
SM	0.310	1.226***	0.931***	-2.023**
	(1.352)	(2.717)	(3.977)	(-2.005)
SMST	1.019***	1.831***	1.783***	-33.435
	(2.653)	(2.586)	(4.614)	(0.000)
*SM*Competition*		-0.209*		
		(-1.856)		
*SMST*Competition*		-0.206		
		(-1.111)		
Observations	24,884	24,884	20,693	4,191

Table 8. Potential reallocation of resources: Unshocked phase-II projects and new drug initiations

The tests in panel A examine the development likelihood of never-shocked phase-II projects owned by active rivals that had recently experienced BTD entry in a market where they were developing a phase-II project. The results are based on the main Cox hazards model specification, which stratifies estimates by market and uses as the analysis time the number of quarter since the beginning of phase-II. The sample includes never-shocked phase-II projects for active rivals. Active rivals are firms that have recently experienced BTD entry to a markets in which they operate were developing a phase-II project. Three variables are used in the tests below to identify the type of rival. *HiComp shock* is a dummy variable equal to one if the rival had experienced BTD entry in a highly competitive market (i.e., with a competition level that is above the median competition level in the full phase-II sample), and equal to zero if they experienced a BTD shock in a low competition market. *HiExp shock* is a dummy variable equal to one if the rival had experienced BTD entry in a market that the rival was highly exposed to (i.e., the rival's exposure was above the median level of firms' market exposure in the full phase-II sample), and is equal to zero if the rival had low exposure to the shocked market. *HiComp_HiExp shock* is a dummy variable equal to one for rivals that had experienced BTD entry in a competitive market *and* where they were highly exposed. The tests reported in columns 1 and 2 (columns 3 and 4) are based on the subsample of rivals' never-shocked projects in low (high) competition markets with a competition level below (above) the median level of competition in the full phase-II sample. z-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. Rival development of unshocked Phase-II projects

	Low focal mkt competition (below sample median)		High focal mkt competition (above sample median)	
	(1)	(2)	(3)	(4)
HiComp_HiExp shock	0.254*	0.479***	-0.335**	-0.276*
	(1.679)	(2.762)	(-2.296)	(-1.744)
HiExp shock		0.167		-0.551**
		(0.852)		(-2.449)
HiComp shock		-0.833***		-0.088
		(-3.528)		(-0.382)
Observations	22,783	22,783	22,770	22,770

Table 8: continued

The tests in panel B examine the initiations of rivals that had recently experienced BTD entry to a market where they were developing a Phase-II project. The table reports OLS estimates of drug initiations conditional on the type of rival. The sample used in the tests below has an observational level of firm-quarter and includes rivals that had recently experienced BTD entry in a market where they were developing a phase-II project. The analysis sample is firm quarter. The dependent variables are *Initiation*, *LowComp init*, and *HiComp init*, and are defined as indicator variables equal to one in the quarter that a rival initiates a drug project, initiates a drug project in a low competition market (below the full drug sample's median of competition level) or initiates a drug project in a high competition market (above the full drug sample's median level of competition), respectively, and is equal to zero otherwise. *HiComp shock* is a dummy variable equal to one if the rival had experienced BTD entry, in one of the last four quarters, in a highly competitive market (i.e., with a competition level that is above the median competition level in the full phase-II sample), and equal to zero otherwise. *HiExp shock* is a dummy variable equal to one if the rival had experienced BTD entry, in the previous 4 quarters, in a market that the rival was highly exposed to (i.e., the rival's exposure was above the median level of firms' market exposure in the full phase-II sample) and is equal to zero otherwise. *HiComp_HiExp shock* is a dummy variable equal to one if for rivals that had experienced in the previous 4 quarters BTD entry in a competitive market and where they were highly exposed. In the first four columns below, the full sample all active rivals' are included. In the last four columns below, the sample is restricted only to rivals that were highly exposed to the market in which they had experienced BTD entry. All regressions include firm and quarter FE and SE clustered by firm. *t*-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

	Full sample			High exposure rival subsample		
Initiation type	*Initiation*	*LowComp init.*	*HiComp init.*	*Initiation*	*LowComp init.*	*HiComp init.*
	(1)	(2)	(3)	(4)	(5)	(6)
HiComp_HiExp shock	0.044***	0.012*	0.005			
	(5.125)	(1.714)	(0.811)			
HiExp shock	-0.041***	-0.021**	-0.028***			
	(-3.491)	(-2.386)	(-3.525)			
HiComp shock	0.018	0.007	0.012	0.038**	0.032***	0.021*
	(1.393)	(0.696)	(1.338)	(2.337)	(2.988)	(1.876)
Observations	18,984	18,984	18,984	9,768	9,768	9,768
R-squared	.247	.203	.220	.216	.145	.163

Table 9. Financial outcomes following BTD shocks

This table displays results from OLS regressions of firm-level financial outcomes following BTD shocks. The sample used in this table includes firms in the full drug sample that matched with the Compustat quarterly fundamentals files. The sample has an observation level of firm-quarter and includes financial information on 1,109 firms in 50 quarters between 2010q1 and 2021q4. The dependent variables are indicated in each column heading. Acquisition is a dummy equal to one if the firm was involved in the acquisition of another firm or drug, in the corresponding quarter. Cash/AT and SG&A/Rev are a firm's quarterly cash holdings divided by total assets, and quarterly sales, general and administrative expenses divided by quarterly sales, respectively. Leverage is equal to total debt divided by total assets. All financial data have been winsorized at the 1% level.
In panel A, the full sample is used, and *BTD shock* is an indicator equal to one if the firm experienced BTD entry in the previous 4 quarters, and zero otherwise. *App BTD shock* is a dummy equal to one if the firm experienced BTD entry in the previous 4 quarters in a market where it has an approved for sale product.
In panel B, the sample is restricted to active rivals that have experienced BTD entry in a market where they were developing a drug project in the previous 4 quarters (columns 1–4) or 8 quarters (columns 5–8). All tests below include firm and year FE and cluster SE by firm. *t*-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

	Acquisition	Cash/AT	SG&A/Rev	Leverage	Acquisition	Cash/AT	SG&A/Rev	Leverage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Full sample of rivals and controls							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BTD rival	-0.026***	0.014	-1.639	-0.046	-0.038***	0.024**	-7.088	-0.088
	(-3.521)	(1.405)	(-0.142)	(-0.391)	(-5.203)	(2.229)	(-0.465)	(-0.703)
App BTD rival					0.079***	-0.062***	10.882	0.280***
					(4.975)	(-4.484)	(1.295)	(4.002)
Observations	26,316	26,143	7,319	26,018	26,316	26,143	7,319	26,018
R-squared	.721	.585	.662	.502	.721	.585	.662	.502

	B. Rivals-only sample							
	Four quarters after rival is shocked				Eight quarters after rival is shocked			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
App BTD rival	0.082***	-0.032***	-15.093	0.214***	0.103***	-0.037***	-9.493	0.202***
	(5.667)	(-2.673)	(-1.392)	(3.942)	(7.436)	(-3.366)	(-1.308)	(4.233)
Observations	8,533	8,509	2,023	8,476	10,861	10,834	2,568	10,790
R-squared	.869	.693	.794	.439	.860	.678	.763	.349

Appendix A. Variable Definitions

Table A1. Drug-, market-, and firm-level variable definitions

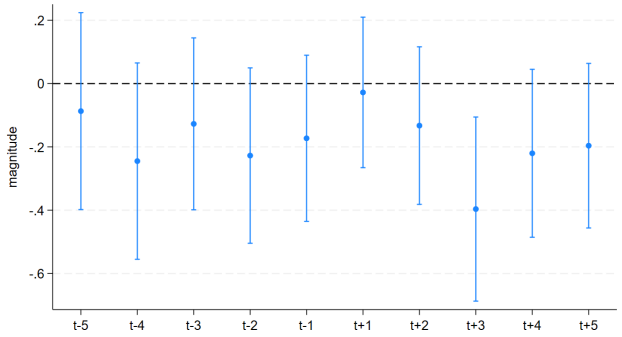
Variable	Definition
	A. Drug-level variables
BTD shock	An indicator equal to one if a drug experiences BTD entry in its target market
Graduation	An indicator equal to one if a phase-II project graduates to phase-III
SMST shock	An indicator equal to one for projects that experience the entry of a BTD drug that targets the same market and uses the same technology (i.e., shares at least one target action)
SM shock	An indicator equal to for projects that experience the entry of a BTD drug that targets the same market but uses a different technology
	B. Market- & firm-market-level variables
Competition	The natural logarithm of the number of drug projects being developed in a market each quarter
Exposure	The number of projects owned by a firm in a market divided by the total number of projects owned by the firm
U.S. China import	The ratio of U.S. imports from China in a given year to U.S. market volume in 1991
	C. Firm-level variables
Acquisition	An indicator equal to one in the quarter that a firm acquires a firm or drug
App BTD shock	An indicator equal to one if the firm experienced BTD entry in a market where it owns an approved for sale product
BTD firm	An indicator equal to one for firms that had received a BTD award for one of its drugs
BTD Rival	An indicator equal to one for firms that experiences BTD entry in one of the markets it operates
Cash/AT	A firm's cash holdings divided by total assets
CiteW Patent	Calculated by weighing each patent by the ratio of that patent's citations relative to all citations by all patents in that industry, then by adding up all citation-weighted patents of a firm that were filed in a given year
HiComp_HiExp shock	An indicator equal to one if a firm experiences BTD entry in a highly competitive market where the firm is highly exposed
HiComp shock	An indicator equal to one if a firm experiences BTD entry in a highly competitive market
HiExp shock	An indicator equal to one if a firm experiences BTD entry where the firm is highly exposed
Initiation	An indicator equal to one in the quarter that a firm initiates a drug project
Leverage	A firm's total debt divided by total assets
Patent an indicator	An indicator equal to one in the quarter that a firm had filed a patent
R&D/AT	A firm's R&D expense divided by total assets
SG&A/Rev	A firm's sales, general and administrative expense divided by total revenues
SM rival	An indicator equal to one for firms with projects that experience the entry of a BTD drug that targets the same market but uses a different technology
SMST rival	An indicator equal to one for firms with projects that experience the entry of a BTD drug that targets the same market and uses the same technology (i.e., shares at least one target action)

Appendix B. Additional Robustness Tests

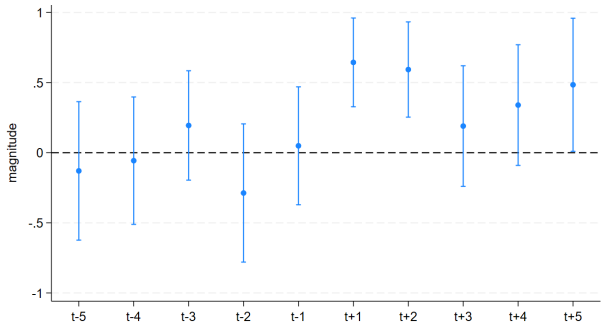
Figure B1. Time trends in phase-II development following BTDs with previously published trial results or patents issued

This figure displays coefficients from a Cox proportional hazards model that is similar to the one used in Figure 2 but restricts the sample of BTD awards to BTD-drugs that either have published trial results or were issued a patent in the 5 years before they were awarded a BTD. The success event, *Graduation*, is an indicator equal to one in the quarter that a project graduates to phase-III, and equal to zero in all quarters where it remains in phase-II. The analysis time is the number of quarters since the start of phase-II. The plotted coefficients are interaction variables between an indicator, ever-BTD shocked, which equals one if a phase-II project ever experiences BTD entry, with annual event time indicators for each of the 5 years before and after BTD entry. The bar caps cover the 95% confidence intervals for each coefficient. The Cox proportional hazards model is stratified by therapeutic market, includes calendar quarter fixed effects, and clusters standard errors by drug project. The analysis sample in Figure 4, panel A, is the full sample of phase-II projects. The sample in panel B (panel C) includes phase-II projects in markets with low (high) competition, that is, markets with competition levels below (above) the median competition level in the full phase-II sample.

(A) Full sample



(B) Low competition subsample



(C) High competition subsample

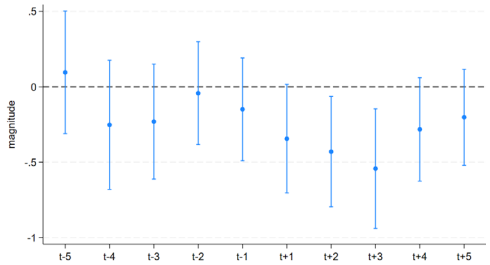


Table B1. Robustness of Table 6 using OLS regressions

The results displayed in this table replicate those of Table 6 using OLS regressions. The dependent variable, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. Competition is calculated each quarter as the natural logarithm of the total number of drug projects in a therapeutic market. In both panels below, the full sample of phase-II projects is used in columns 1 and 2, and in columns 3 and 4, the full sample is partitioned by the level of competition; projects in markets below (above) the median level of competition are used in column 3 (column 4). In panel A, the variable *BTD shock* is an indicator equal to one for all phase-II projects that reside in a market that had experienced BTD entry, and equal to zero otherwise. In panel B, the variable SM is an indicator equal to one if the focal project targets a market that had experienced BTD entry and but uses a different technology, than that used by any of the drugs that were awarded a BTD in that market. SMST is an indicator equal to one if the focal project had experienced BTD entry into its market and uses at least one target action (i.e., technology) that is also used by any of the drugs that were awarded a BTD in the same market. To control for the right-censoring problem, the sample excludes projects that report the start of phase-II development on or after 2020q1. The regressions below include the following fixed effects: calendar quarter, market and project age in phase-II. Standard errors are clustered by drug project. *t*-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. BTD shocks and phase-II development

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
BTD shock	-0.001	0.010***	0.005***	-0.002**
	(-1.058)	(3.083)	(2.723)	(-2.205)
Competition		-0.000		
		(-1.109)		
*BTD shock*Competition*		-0.002***		
		(-3.458)		
Observations	181,842	181,842	92,612	89,216
R-squared	.110	.110	.111	.136

B. BTD shocks and phase-II development conditional on the type of rival

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
SMST	0.006**	0.025**	0.012*	0.006**
	(2.319)	(2.118)	(1.860)	(2.071)
SM	-0.001*	0.008**	0.004**	-0.002***
	(-1.774)	(2.569)	(2.281)	(-2.778)
Competition		-0.000		
		(-1.206)		
*SMST*Competition*		-0.004*		
		(-1.765)		
*SM*Competition*		-0.002***		
		(-3.085)		
Observations	181,842	181,842	92,612	89,216
R-squared	.110	.110	.111	.136

Table B2. Robustness of Table 6 using logit model

The results displayed in this table replicate those of Table 6 using logit regressions. The dependent variable, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. Competition is calculated each quarter as the natural logarithm of the total number of drug projects in a therapeutic market. In both panels below, the full sample of phase-II projects is used in columns 1 and 2, and in columns 3 and 4, the full sample is partitioned by the level of competition; projects in markets below (above) the median level of competition are used in column 3 (column 4). In panel A, the variable *BTD shock* is an indicator equal to one for all phase-II projects that reside in a market that had experienced BTD entry, and equal to zero otherwise. In panel B, the variable SM is an indicator equal to one if the focal project targets a market that had experienced BTD entry and but uses a different technology, than that used by any of the drugs that were awarded a BTD in that market. SMST is an indicator equal to one if the focal project had experienced BTD entry into its market and uses at least one target action (i.e., technology) that is also used by any of the drugs that were awarded a BTD in the same market. To control for the right-censoring problem, the sample excludes projects that report the start of phase-II development on or after 2020q1. The regressions below include calendar quarter fixed effects with robust standard errors. *t*-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. BTD shocks and phase-II development

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
BTD shock	-0.195***	1.763***	0.506***	-0.552***
	(-2.585)	(9.053)	(4.688)	(-5.054)
Competition		-0.018		
		(-0.920)		
*BTD shock*Competition*		-0.399***		
		(-10.109)		
Observations	178,410	178,410	91,102	87,308

B. BTD shocks and phase-II development conditional on the type of rival

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
SMST	0.553***	1.771***	1.071***	0.329*
	(4.370)	(4.048)	(5.381)	(1.953)
SM	-0.314***	1.808***	0.425***	-0.702***
	(-3.933)	(8.883)	(3.734)	(-6.061)
Competition		-0.018		
		(-0.927)		
*SMST*Competition*		-0.244***		
		(-2.774)		
*SM*Competition*		-0.434***		
		(-10.513)		
Observations	178,410	178,410	91,102	87,308

Table B3. Phase-II development, BTD shocks, and policy exposure

The tests in this table examine the effect of BTD shocks on the development likelihood of phase-II projects conditional on the extent of a market's exposure to BTD policy. They use the same Cox Proportional Hazards model specifications as those used in Table 6, where estimates are stratified by market and the analysis time is equal to the number of quarters since the start of phase-II trials. The success event, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. *Policy exposure*, as defined by Hermosilla (2024), is a variable with values between zero and one that measures the extent to which the FDA considers a medical condition (i.e., therapeutic market) serious or life-threatening. It is essentially a market-level measure of the likelihood that a BTD designation is granted within a market. The analysis sample is constructed by matching the full phase-II sample to policy exposure data, then dividing the sample into subsamples conditional on the extent of policy exposure. In the first (last) four columns, results are reported from analyses that use the subsample of phase-II projects in markets with low (high) policy exposure - less than (greater than) or equal to 50%. Columns 3 and 7 (columns 4 and 8) report results from using the sample of phase-II projects in markets with competition levels below (above) the median level of competition in the full sample. z-statistics reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. Using the BTD shock variable

	Low policy exposure				**High policy exposure**			
	Full low policy exposure Sample		Market competition		Full high policy exposure Sample		Market competition	
			Low	High			Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BTD shock	0.322***	1.545***	0.764***	-0.646***	-0.113	1.314***	0.304*	-0.469***
	(3.264)	(4.851)	(7.136)	(-2.907)	(-1.049)	(2.710)	(1.745)	(-4.015)
*BTD shock*Competition*		-0.303***				-0.285***		
		(-3.940)				(-2.986)		
Observations	73,288	73,288	49,736	23,552	66,153	66,153	20,987	45,166

B. Using SM and SMST variables to identify rivals

	Low policy exposure				**High policy exposure**			
	Full low policy exposure Sample		Market competition		Full high policy exposure Sample		Market competition	
			Low	High			Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SMST	0.864***	2.673***	1.372***	-36.109***	0.493***	1.261	0.738*	0.322*
	(4.133)	(5.367)	(6.619)	(-169.554)	(2.771)	(1.453)	(1.773)	(1.665)
SM	0.239**	1.233***	0.649***	-0.552**	-0.250**	1.497***	0.248	-0.642***
	(2.242)	(3.346)	(5.458)	(-2.486)	(-2.157)	(2.879)	(1.344)	(-5.048)
Competition		0.032				0.073		
		(1.058)				(1.370)		
*SMST*Competition*		-0.474***				-0.156		
		(-3.688)				(-0.951)		
*SM*Competition*		-0.244***				-0.351***		
		(-2.795)				(-3.424)		
Observations	73,288	73,288	49,736	23,552	66,153	66,153	20,987	45,166

Table B4. Robustness of Table 6, alternative sample 1: Matched sample

The tests in this table replicate those of Table 6 using an alternative sample that matches each shocked project to a similar project. The tests below use the same Cox Proportional Hazards model specifications as those used in Table 6, where estimates are stratified by market and the analysis time is equal to the number of quarters since the start of phase-II trials. The success event, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. The sample is constructed by randomly matching each ever-BTD-shocked project (treated project) in the full phase-II sample to a single never-shocked control project from a pool of potential control matches. Control projects must satisfy the following criteria. First, at the drug level, a control must have started phase-II development within 5 years of the treated drug. Second, at the market level, a control must target a market in the same quartile of competition as that of the treated drug. Third, at the firm-market level, the control firm's exposure to the control project's market must be in the same quartile as that of the treated firm's exposure to the treated project's market. Exposure is measured as the number of projects a firm develops in a market divided by the total number of projects developed by the same firm. Finally, at the firm level, the size of the control firm developing the control project must be in the same quartile as that of the treated firm developing the treated project. Size is measured as the total number of projects owned by the firm. z-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. BTD shocks and phase-II development

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
BTD shock	-0.037	1.621***	1.103***	-0.601***
	(-0.355)	(5.249)	(7.347)	(-4.676)
Competition		0.112**		
		(1.993)		
*BTD shock*Competition*		-0.352***		
		(-5.039)		
Observations	154,844	154,844	39,921	114,923

B. BTD shocks and phase-II development conditional on the type of rival

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
SMST	0.587***	1.787***	1.534***	0.136
	(4.079)	(3.736)	(6.978)	(0.752)
SM	-0.155	1.687***	1.039***	-0.761***
	(-1.434)	(5.261)	(6.763)	(-5.698)
Competition		0.114**		
		(2.007)		
*SMST*Competition*		-0.251**		
		(-2.488)		
*SM*Competition*		-0.393***		
		(-5.434)		
Observations	154,844	154,844	39,921	114,923

Table B5. Robustness of Table 6, alternative sample 2: Excluding cancer markets

The tests in this table replicate those of Table 6 using an alternative sample that excludes all drugs intended for cancer. The tests below use the same Cox Proportional Hazards model specifications as those used in Table 6, where estimates are stratified by market and the analysis time is equal to the number of quarters since the start of phase-II trials. The success event, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. Drugs targeting cancer-related markets are identified if the first letter of their ICD-10 code begins with "C." z-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. BTD shocks and phase-II development

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
BTD shock	0.092	1.227***	0.591***	-0.553***
	(1.001)	(5.157)	(4.831)	(-3.570)
Competition		-0.002		
		(-0.069)		
*BTD shock*Competition*		-0.260***		
		(-5.007)		
Observations	122,901	122,901	76,296	46,605

B. BTD shocks and phase-II development conditional on the type of rival

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
SMST	0.522***	1.452***	1.080***	-0.140
	(3.230)	(3.095)	(5.184)	(-0.532)
SM	0.007	1.233***	0.513***	-0.660***
	(0.077)	(4.892)	(4.007)	(-3.904)
Competition		-0.002		
		(-0.085)		
*SMST*Competition*		-0.204**		
		(-1.988)		
*SM*Competition*		-0.284***		
		(-5.127)		
Observations	122,901	122,901	76,296	46,605

Table B6. Phase-II development tests conditional on whether the BTD drug is owned by a biotech versus big pharma firm

This table displays results from a hazard model estimating the likelihood of phase-II graduation conditional on BTD entry (our main tests). The sample used here is the same one used in the main table (first four columns of Table 6), however, it is partitioned by whether the first BTD awarded in the market was owned by a smaller biotech (first four columns) or a big pharma firm (last 4 columns). Biotech firms are defined if a firm has no approved products (i.e., if it is a precommercial firm), with big pharma the corollary sample. Note that there are 4,422 (2,105) projects that are shocked by BTD that is owned by a big pharma (small biotech) and correspond to 70,313 (34,503) project-quarter observations. There are 5,511 control projects that correspond to 90,920 project-quarter observations.

	First BTD in mkt awarded to small biotech + controls				First BTD in mkt awarded to a big pharma firm + Controls			
	Full sample		Low comp	Hi comp	Full sample		Low comp	Hi comp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BTD shock	-0.351***	0.824**	0.274*	-0.637***	-0.266***	2.245***	0.585***	-0.622***
	(-3.673)	(2.372)	(1.812)	(-4.993)	(-4.103)	(10.570)	(6.476)	(-6.460)
Competition		0.041**				-0.014		
		(2.091)				(-0.758)		
*BTD shock*Competition*		-0.248***				-0.505***		
		(-3.497)				(-11.253)		
Observations	125,423	125,423	78,542	46,881	161,233	161,233	86,923	74,310

Table B7. Robustness of Table 6, alternative competition measure 1: Sales-based HHI

The tests in this table replicate those of Table 6 using an alternative measure for competition. The tests below use the same Cox Proportional Hazards model specifications as those used in Table 6, where estimates are stratified by market and the analysis time is equal to the number of quarters since the start of phase-II trials. The success event, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. The alternative competition measure used in these tests is a sales-based HHI index that is created using Drug sales data from the Cortellis database. Columns 3 and 4 partition the sample by the median of the HHI index in the full sample. In column 3, the subsample used is drugs in markets that are competitive (i.e., low HHI, that lies below the median), and in column 4, the projects include those in concentrated markets with HHI above the median. z-statistics are reported in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. BTD shocks and phase-II development

	Full sample		HHI level	
			Low	High
	(1)	(2)	(3)	(4)
BTD shock	-0.111	-0.409***	-0.262**	0.282**
	(-1.455)	(-3.052)	(-2.375)	(2.513)
HHI (concentration)		-0.327***		
		(-2.725)		
*BTD shock*Concentration*		0.584**		
		(2.538)		
Observations	146,444	146,444	78,883	67,561

B. BTD shocks and phase-II development conditional on the type of rival

	Full sample		HHI level	
			Low	High
	(1)	(2)	(3)	(4)
SMST	0.545***	0.300	0.530***	0.853***
	(4.388)	(1.357)	(3.286)	(4.072)
SM	-0.246***	-0.616***	-0.466***	0.206*
	(-3.007)	(-4.247)	(-3.886)	(1.756)
HHI		-0.332***		
		(-2.753)		
*SMST*HHI*		0.493		
		(1.137)		
*SM*HHI*		0.728***		
		(2.975)		
Observations	146,444	146,444	78,883	67,561

Table B8. Robustness of Table 6: Alternative competition measure 2: # of firms in mkt (equal-weighted)

The tests in this table replicate those of Table 6 using an alternative measure for competition. The tests below use the same Cox Proportional Hazards model specifications as those used in Table 6, where estimates are stratified by market and the analysis time is equal to the number of quarters since the start of phase-II trials. The success event, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. The competition measure here is the equal-weighted number of firms in a market in each quarter. z-stats are presented in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. BTD shocks and phase-II development

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
BTD shock	0.013	1.164***	0.430***	-0.241**
	(0.181)	(5.340)	(4.114)	(-2.468)
Competition		-0.020		
		(-0.793)		
*BTD shock*Competition*		-0.265***		
		(-5.321)		
Observations	195,736	195,736	97,926	97,810

B. BTD shocks and phase-II development conditional on the type of rival

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
SMST	0.621***	1.113**	0.876***	0.475***
	(5.132)	(2.563)	(4.641)	(2.970)
SM	-0.101	1.235***	0.362***	-0.399***
	(-1.348)	(5.345)	(3.286)	(-3.839)
Competition		-0.020		
		(-0.820)		
*SMST*Competition*		-0.109		
		(-1.127)		
*SM*Competition*		-0.310***		
		(-5.846)		
Observations	195,736	195,736	97,926	97,810

Table B9. Robustness of Table 6, Alternative competition measure 3: # of firms in mkt (value-weighted by firm size)

The tests in this table replicate those of Table 6 using an alternative measure for competition. The tests below use the same Cox Proportional Hazards model specifications as those used in Table 6, where estimates are stratified by market and the analysis time is equal to the number of quarters since the start of phase-II trials. The success event, *Graduation*, is an indicator equal to one in the quarter that a phase-II project graduates to phase-III, and equal to zero in all other quarters. The competition measure here is a weighted count of firms in a market with weights assigned by firm size. The measure is constructed as follows. In each quarter, all firms are ranked in ascending order by their total number of projects (the first firm in this ordering is the smallest, and the last is the largest). Next, the relative weight of a firm in a quarter is calculated by dividing the order of the firm by the highest order of any firm in the same quarter (e.g., if 720 firms were active in a given quarter, The largest firm's relative weight would be 720/720=1 and the smallest is 1/720=0.14%). Finally, in each market, the relative weights of each firm is computed every quarter. This weighted-sum becomes the competition measure that is used in the tests below. z-stats are presented in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

A. BTD shocks and phase-II development

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
BTD shock	0.013	1.194***	0.377***	-0.322***
	(0.181)	(5.499)	(3.647)	(-3.453)
Competition		-0.012		
		(-0.493)		
*BTD shock*Competition*		-0.274***		
		(-5.464)		
Observations	195,736	195,736	97,895	97,841

B. BTD shocks and phase-II development conditional on the type of rival

	Full sample		Competition level	
			Low	High
	(1)	(2)	(3)	(4)
SMST	0.621***	1.148***	0.832***	0.510***
	(5.132)	(2.684)	(4.379)	(3.345)
SM	-0.101	1.260***	0.306***	-0.478***
	(-1.348)	(5.457)	(2.809)	(-4.801)
Competition		-0.013		
		(-0.527)		
*SMST*Competition*		-0.118		
		(-1.228)		
**Competition*		-0.317***		
		(-5.943)		
Observations	195,736	195,736	97,895	97,841

Table B10. A comparison between the effects of blockbuster and non-BB BTD entrance on market

The table displays results from OLS regressions of market-level activity variables on BTD entry conditional on blockbuster status. The sample analysis has an observation level of market-quarter. All markets included eventually experience BTD entry of projects that eventually receive FDA approval. Markets that experience BTD entry of projects that are not approved by the end of the sample are dropped. This constraint is necessary because it allows us to define blockbuster drugs, and projects without FDA approval do not have sales data. Moreover, this allows for a cleaner comparison between the effects of blockbuster BTD entrance and that of non-BB drugs. There are 118 markets in the sample, 49 experience BB BTD entry and 69 experience non-BB BTD entry.

Post-BTD is a dummy equal to one starting in the first quarter after a BTD enters and until the end of the sample. Blockbuster is a dummy equal to one for markets that eventually experience BB BTD entry.

The dependent variables are (a) Initiations, which counts the number of new project initiations in a market-quarter; (b) Approvals, which counts the number of projects that received FDA approval in a market-quarter; (c) Mkt competition, which is our original competition measure that counts the total number of projects in a market-quarter; (d) Mkt HHI, which is the sales-based HHI index in a market-quarter; (e) Mkt Sales, which is the total sales in a market-quarter; and (f) # of patents, which is count of patents in a market-quarter.

All dependent and independent variables are defined at the ICD-10 second subchapter level. All regressions include the following FEs: calendar quarter and market (ICD-10 at the first subchapter level to allow the *Blockbuster* dummy to be estimated and not omitted). SE are clustered at the ICD-10 second subchapter level.

Dependent var	*Initiations*	*Approvals*	*Mkt comp*	*Mkt HHI*	*Mkt sales*	*# of patents*
	(1)	(2)	(3)	(4)	(5)	(6)
			A. Pooled sample			
	(1)	(2)	(3)	(4)	(5)	
Post-BTD	-0.727*	0.074**	-14.413	-0.100**	51.386	0.043
	(-1.671)	(2.419)	(-1.239)	(-2.498)	(0.453)	(0.054)
Blockbuster	0.911	0.036	37.867	-0.154*	587.308**	6.213
	(0.556)	(0.597)	(1.009)	(-1.873)	(2.115)	(1.285)
*Post-BTD*Blockbuster*	2.554**	0.084**	45.620*	0.028	501.290***	5.286***
	(2.281)	(2.339)	(1.867)	(0.468)	(2.855)	(3.336)
Observations	5,506	5,506	5,506	3,373	4,215	5,506
R-squared	.640	.162	.800	.679	.644	.833
			B. Sample of mkts that experience blockbuster BTD entry			
	(1)	(2)	(3)	(4)	(5)	(6)
Post-BTD	0.551	0.161***	-8.724	-0.097**	396.236**	2.157***
	(0.718)	(4.052)	(-0.477)	(-2.183)	(2.374)	(2.796)
Observations	2,352	2,352	2,352	1,695	2,090	2,352
R-squared	.661	.149	.760	.548	.618	.863
			C. Sample of mkts that experience nonblockbuster BTD entry			
	(1)	(2)	(3)	(4)	(5)	(6)
Post-BTD	-0.201	0.054	7.006**	-0.086**	76.693*	0.557
	(-0.781)	(1.486)	(2.130)	(-2.182)	(1.809)	(1.216)
Observations	3,154	3,154	3,154	1,678	2,125	3,154
R-squared	.661	.203	.924	.808	.697	.909

Table B11. Phase-II development tests conditional on blockbuster status of BTD drug

This table displays results from a hazard model estimating the likelihood of phase-II graduation conditional on BTD entry (our main tests). The sample of projects target the same markets described in Table 1, that is, for a project to be included, it must target a market that had experienced BTD entry of a project that had eventually received FDA approval. The first four (last four) columns report results from tests that restrict the sample to markets that had experienced the entry of a Blockbuster (non-BB) BTD drug.

	Blockbuster BTD				*Non-BB BTD*			
	Full sample		Low comp	Hi comp	Full sample		Low comp	Hi comp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BTD shock	-0.017	1.378***	0.461**	-0.021	-0.035	1.515***	0.474**	-0.455**
	(-0.127)	(2.624)	(2.191)	(-0.119)	(-0.256)	(2.822)	(2.498)	(-2.222)
Competition		-0.246***				0.071		
		(-2.656)				(0.775)		
*BTD shock*Competition*		-0.238**				-0.334***		
		(-2.172)				(-2.931)		
Observations	48,541	48,541	9,909	38,632	22,830	22,830	8,372	14,458