Innovation-for-buyout in Drug Development*

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Abstract

We study how acquisition prospects shape biotech startups' entry and drug development. Linking drug-pipeline records with acquisition data, we find that pharmaceutical acquisitions are associated with greater startup entry and subsequent development, especially in early clinical phases. We develop a dynamic game in which startups weigh the potential value of a buyout against competition from rival projects. The model provides a framework for assessing how restrictions on startup acquisitions may affect entry and innovation.

1 Introduction

Biotech companies have become increasingly important sources of pharmaceutical innovation. Recent breakthroughs include Spikevax, an mRNA-based COVID-19 vaccine developed by Moderna. Lo and Thakor (2022) show the biotech companies, typically smaller and much more R&D intensive than conventional pharmaceutical companies, has become increasingly prominent: while in 2000 only 4 out of 30 top-selling drugs came from biotech companies, in 2018 20 of the top 30 originated by biotech. Understanding the behavior of those new starups, particularly their entry and exit decisions, is thus critical for any policy discussion regarding the recent drug innovation.

This paper examines how acquisition prospects shape biotech startups' entry and innovation decisions. The pre-acquisition incentives are important in understanding the biotech

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industry, given the nature of drug development. Drug development is costly and highly uncertain, and early-stage startups often lack revenue-generating products and face severe financing constraints. Hence, a successful *exit* path for many startups is viewed as getting acquired[1]. The expected returns from a potential acquisition may therefore influence both whether startups enter and how much they put effort in innovation—the entry-for-buyout and innovation-for-buyout incentives.

To examine how the acquisition market affects the biotech startup entry, we link drug pipeline data from Pharmaprojects to M&A transactions compiled from SDC Platinum and PitchBook. PharmaProjects records the universe of drug projects from the date of initial registration as drug candidates to updates on development status throughout clinical trials and FDA approval. Linking these records to M&A transactions allows us to examine acquisition activity alongside changes in firms' drug portfolios and project development across drug categories.

Our dataset exhibits strong positive correlation between acquisitions taking place and new startup entry. A broad category of drugs have an upward trend in acquisitions and startup entry, where oncology shows the starkest increase. This pattern is further confirmed by our fixed effect regressions. We also find that the clinical trial outcomes responds to the entry as well. Especially, we observe significant increase in early phase development of drugs, namely phase I and phase II, in response to increase in acquisition events.

Motivated by this reduced form findings, we develop a theoretical model of entry and drug development game with acquisition markets. Potential entrants decide whether to start a new drug project, expecting that they may meet and bargain with large non-startup firms over acquisitions. The opportunity of being acquired raises the ex-ante expected payoff of entry and proceeding the clinical trials. At the same time, however, acquisition makes the incumbent's portfolio richer and may stiffen the competition. The implication of the acquisition markets for the innovation process depends on how those two mechanism interact each other.

This paper connects to several strands of the literature. First, this paper relates to the empirical studies on how merger affects the pharmaceutical industry. Many papers discuss the post-acquisition effect on the drug development process. Cunningham, Ederer and Ma (2021) find a *killer acquisitions*, where acquirers terminate the acquired projects that are overlapped with their existing projects, providing new empirical perspective to merger policy from the angle of innovation dynamics. Malek, Seldeslachts and Veugelers (2025) consider the technology space as well as product market position to measure the acquirer-target

[1]In fact, Eisfeld (2025) shows M&A accounts for 50% of the successful exits of biotech startups alongwith IPO.

proximity. They find more post-acquisition termination when an acquired project is far from development completion, while the proximity in technology space can make acquisition pro-innovation. Wabiszewski (2025) builds a structural model of drug development and acquisition game, finding both diseconomies and economies of scale across different phases. We complement this strand of literature by providing a close examination of the pre-merger effect on entrants incentive, Entry-for-buyout.

Second, this paper builds on the discussion of Entry-for-buyout and its application to startup. Since Rasmusen (1988), a substantial body of research has explored how merger policies can affect pre-acquisition behavior, both the level of investment (Norbäck and Persson, 2012; Mason and Weeds, 2013; Phillips and Zhdanov, 2013; Jaunaux, Lefouili and Sand-Zantman, 2017; Hollenbeck, 2020; Kamepalli, Rajan and Zingales, 2021; Bisceglia et al., 2024) and the direction of innovation (e.g., Katz (2021), Callander and Matouschek (2022), Kamepalli, Rajan and Zingales (2021), Motta and Shelegia (2021), Dijk, Moraga-González and Motchenkova (2024)). The empirical study in this regard is relatively scarce. Closest to our paper is Eisfeld (2025), who studies the entry-for-buyout and kill-zone effect on software startups' entry decision by estimating the structural model. She finds that banning acquisitions can hinder startup entry, highlighting the relevance of pro-competitive implication of merger prospect. Our paper focuses on pharmaceutical industries, and considers the pre-acquisition behavior of startups in both entry and innovation phase.

2 Data

2.1 Data Sources

First, we obtain data on drug projects from Pharmaprojects. For each drug, it records the originating firm, the therapeutic classes, and dated development events such as the start of each clinical phase. Second, we obtain data on completed acquisitions from PitchBook and SDC Platinum. Both sources report the target, the acquirer, the deal date, and the acquirer's industry. We merge targets and acquirers with Pharmaprojects firms by firm name.

2.2 Descriptive Statistics

We define a market as a primary therapeutic class in Pharmaprojects and observe each market annually. The data cover 162 markets from 1989 to 2015, or 4,374 market-years. Table 1 summarizes the variables in the analysis. A startup is a firm whose first drugs appear in Pharmaprojects and has no approved or launched drug and fewer than 100 active drugs. An acquirer is a pharmaceutical firm if SDC or PitchBook places it in the pharmaceutical or

biotechnology industry, or if it holds active drugs in Pharmaprojects. An average market-year has about two entrant startups, 20 existing startups, and 0.3 acquisitions of startups by pharmaceutical firms.

Table 1: Descriptive Statistics

	Mean	SD	Median	Min	Max
Entrant startups	1.92	5.49	0	0	113
Existing startups	19.84	52.60	5	0	1,049
Startup acquisitions, all acquirers	0.47	1.21	0	0	18
Startup acquisitions, pharmaceutical acquirers	0.32	0.88	0	0	12
Active drugs	102.93	286.36	28	0	5,791
Startup drugs first reaching Phase I	0.75	2.52	0	0	58
Startup drugs first reaching Phase II	0.49	1.52	0	0	25
Startup drugs first reaching Phase III	0.12	0.49	0	0	12

Notes: The unit of observation is a market-year, where a market is a primary therapeutic class in Pharmaprojects. The sample covers 162 markets from 1989 to 2015, or 4,374 market-years. A startup is a firm whose first drugs appear in Pharmaprojects and has no approved or launched drug and fewer than 100 active drugs. A startup enters in the year its first drug appears in Pharmaprojects, and we follow it until its first acquisition or initial public offering. An acquirer is a pharmaceutical firm if SDC or PitchBook places it in the pharmaceutical or biotechnology industry, or if it holds active drugs in Pharmaprojects.

2.3 Trends in Entry and Acquisitions

Startup entry and acquisitions of startups by pharmaceutical firms both rose over the sample period. Figure 1 plots the annual numbers of entrant startups and startup acquisitions for the six largest broad therapeutic classes. There are two takeaways from this figure. First, entry and acquisitions each are growing. Summed over the six classes, entry rises from about 70 per year in 1989–1993 to about 450 per year in 2011–2015, and acquisitions rise from about 4 to about 35. Second, the classes rank similarly in the two numbers. Over the sample period, Oncology has the most entry and the most acquisitions, and Cardiovascular and Endocrine have the least. This observational pattern motivates our reduced-form analysis.

3 Reduced-Form Evidence

Motivated by this pattern, we regress entry and drug development in a market on acquisitions in that market. For market m and year t, we estimate

$$Y_{m,t+h} = \phi_h A_{mt} + \psi_h \log(1 + N_{mt}) + \mu_m + \lambda_t + u_{m,t+h}, \tag{1}$$

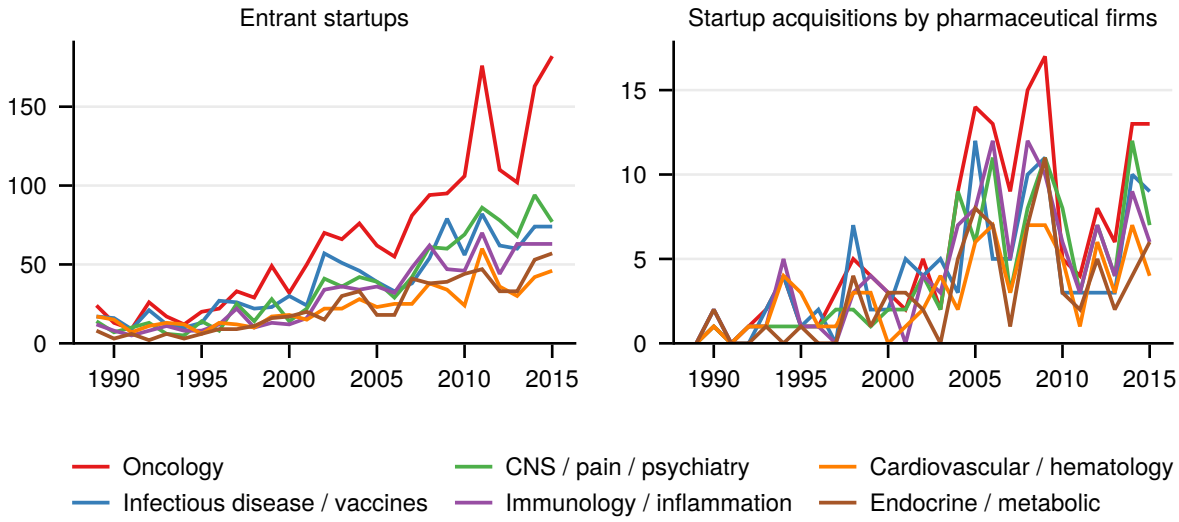


Figure 1: Entry and Acquisitions by Therapeutic Class

Notes: The left panel plots the annual number of entrant startups and the right panel plots the annual number of startups acquired by pharmaceutical firms, 1989–2015. Each line is one of the six broad therapeutic classes with the most entrant startups. A broad class groups primary therapeutic classes, and a startup with drugs in several broad classes counts once in each. Table 1 defines startups, entry, and pharmaceutical firms.

where A_{mt} is the number of startups acquired by pharmaceutical firms and N_{mt} is the number of existing startups. The terms μ_m and λ_t are market and year fixed effects, and standard errors are clustered by market. The outcome $Y_{m,t+h}$ is either the number of entrant startups at $h \in \{0, 1, 3, 5\}$ or the number of startup drugs first reaching Phase I, II, or III at $h = 1$.

The coefficient ϕ_h compares market-years with more acquisitions than usual for that market and year. The coefficients are conditional correlations, not causal effects, because acquisitions may concentrate where opportunities are growing. To control for this market growth effect at least partially, we include the number of existing startups in our regression.

Table 2 shows that acquisitions by pharmaceutical firms are positively correlated with entry. One more acquisition corresponds to 1.8 more entrant startups in the same year and 1.5 more in the next year. These magnitudes are large relative to the mean of about two entrants per market-year. The correlation persists three and five years later.

Table 3 shows that acquisitions by pharmaceutical firms are also positively correlated with drug development by startups. One more acquisition corresponds to 0.84 more startup drugs first reaching Phase I, against a mean of 0.77. The coefficient for Phase II is 0.49, and the coefficient for Phase III is 0.09. The coefficient declines at later phases, where less uncertainty about the drug remains. This decline is consistent with acquisition prospects

mattering most for early development decisions.

These correlations suggest that acquisition prospects could affect startup entry and drug development decisions, but acquisitions also change the competition that startups face. This motivates the structural model in Section 4, which separates buyout incentives from competitive effects.

Table 2: Acquisitions and Entry

	t	$t+1$	$t+3$	$t+5$
Acquisitions by pharmaceutical firms	1.846***	1.549***	1.926**	1.895**
	(0.545)	(0.465)	(0.802)	(0.744)
Log(1 + existing startups)	1.303***	1.485***	1.346***	1.356***
	(0.205)	(0.254)	(0.193)	(0.186)
Mean of dependent variable	1.92	1.96	2.08	2.21
Observations	4,374	4,212	3,888	3,564
Markets	162	162	162	162
Within R-squared	0.197	0.168	0.206	0.208
Market and year FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is the number of entrant startups in the market in the year shown in each column. Standard errors clustered by market are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Acquisitions and Subsequent Drug Development

	Phase I	Phase II	Phase III
Acquisitions by pharmaceutical firms	0.842***	0.486***	0.086*
	(0.263)	(0.117)	(0.048)
Log(1 + existing startups)	0.680***	0.450***	0.124***
	(0.098)	(0.062)	(0.020)
Mean of dependent variable	0.77	0.50	0.13
Observations	4,212	4,212	4,212
Markets	162	162	162
Within R-squared	0.165	0.161	0.052
Market and year FE	Yes	Yes	Yes

Notes: The dependent variable is the number of startup drugs that first reach the phase shown in each column in year $t+1$. Standard errors clustered by market are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4 Model

We develop a dynamic game of entry, drug development, and acquisition to quantify how acquisition opportunities shape startups' entry and development decisions. Potential entrants

decide whether to start a new drug project. Startups then bargain with large non-startup firms over acquisitions and decide whether to continue development.

The model separates two channels through which acquisitions affect startups. First, acquisition opportunities raise the expected payoff from entry and development. Second, market competition shifts this payoff, because rival projects lower the value of a successful drug.

4.1 Setup

Time is discrete, each period is a quarter, and each therapeutic class is an independent market. We index periods by $t = 0, 1, \ldots$ and denote the discount factor by β. We index markets by m. Each startup operates in a single market, so startup-level variables carry only the indices i and t.

There are two types of firms: startups and non-startups. Each startup owns a single lead drug project. We define non-startups as firms in a fixed set of potential acquirers. We index startups by i and non-startups by $b \in B$.

A project's state consists of its development phase and the number of periods it has spent in that phase. The phase is $y_{it} \in \{1, 2\}$ for Phase I and Phase II, and the duration is h_{it}. We summarize the process after Phase II success by a terminal payoff. We choose to limit the development stage within these first two stages of trials, as most startups do not have enough funding to proceed to Phase III and FDA approval without the means of M&A, licensing, or IPO.

State variables for startups are the number of competing projects by development stage and ownership. For each type, the numbers of projects are

$$\mathbf{n}_{mt}^{\text{startup}} = (n_{1mt}^{\text{startup}}, n_{2mt}^{\text{startup}}, n_{3mt}^{\text{startup}}), \qquad \mathbf{n}_{mt}^{\text{non-startup}} = (n_{1mt}^{\text{non-startup}}, n_{2mt}^{\text{non-startup}}, n_{3mt}^{\text{non-startup}}),$$

where the first two elements are the numbers of Phase I and Phase II projects and the third is the number of projects past Phase II success. These vectors and market characteristics $\mathbf{X}_{mt}$ make up the market state $M_{mt} = (\mathbf{n}_{mt}^{\text{startup}}, \mathbf{n}_{mt}^{\text{non-startup}}, \mathbf{X}_{mt})$. The state of startup i is $S_{it} = (y_{it}, h_{it}, M_{mt})$.

The number of non-startup projects evolves through an exogenous component and an endogenous inflow of acquired startup projects. Let $\mathbf{a}_{mt}$ denote the number of startup projects acquired in period t, by phase. The acquired projects are added to $\mathbf{n}_{mt}^{\text{non-startup}}$, which then evolves with market characteristics according to

$$G^{\text{market}}\left(\mathbf{n}_{m,t+1}^{\text{non-startup}}, \mathbf{X}_{m,t+1} \mid \mathbf{n}_{mt}^{\text{non-startup}} + \mathbf{a}_{mt}, \mathbf{X}_{mt}\right).$$

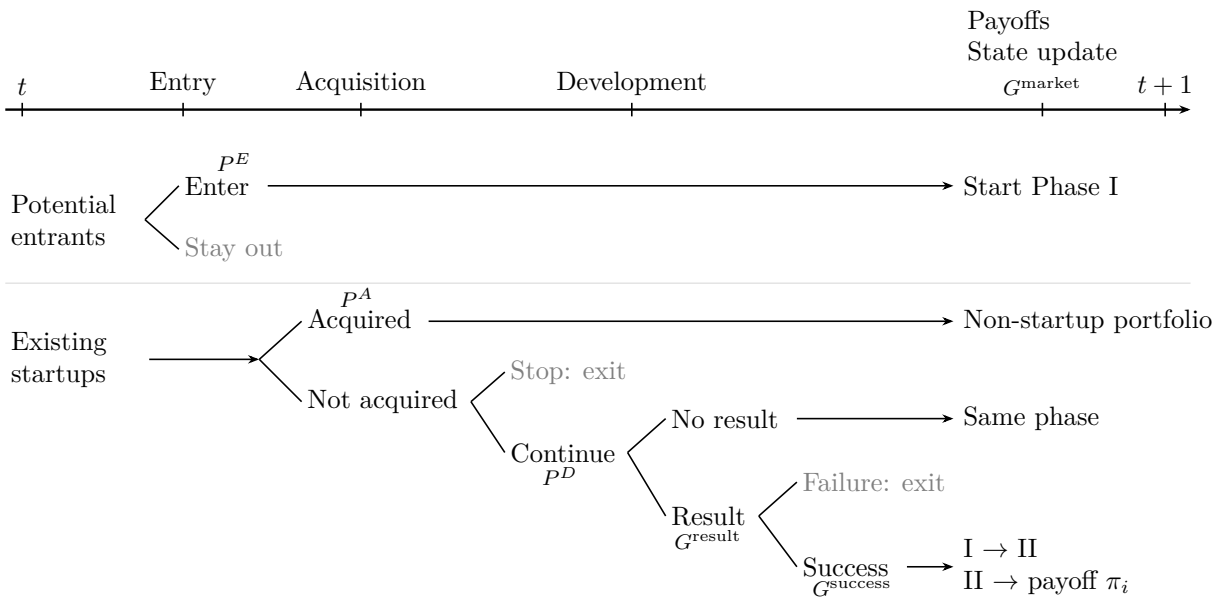


Figure 2: Within-period timing

After an acquisition, the project therefore follows the same exogenous process as other non-startup projects.

A fixed number of potential entrants arrive each period. We set this number to the maximum number of entrants observed in a market-period, following Eisfeld (2025).

4.2 Timing

Each period proceeds in four stages: entry, acquisition, development, and the realization of payoffs and state transitions. Figure 2 summarizes the sequence. Potential entrants first decide whether to enter. An entrant pays the entry cost and starts Phase I in the next period. Each existing startup then bargains with an acquirer. Unacquired startups next decide whether to continue development, and trial results arrive. Finally, terminal payoffs realize and the market state updates.

4.3 Terminal Profits

A startup whose project succeeds in Phase II receives a terminal payoff that summarizes the value of late-stage development and commercialization. We interpret this payoff as the expected value of the project from Phase III onward, not as a per-period profit. The startup then leaves the model, and its project is included in n_{3mt}^{startup}.

The terminal payoff is linear in the number of competing projects and in market charac-

teristics:

$$\pi_i(S_{it}) = \alpha_m + (\boldsymbol{\alpha}^{\text{startup}})'\mathbf{n}_{mt}^{\text{startup}} + (\boldsymbol{\alpha}^{\text{non-startup}})'\mathbf{n}_{mt}^{\text{non-startup}} + (\boldsymbol{\alpha}^{X})'\mathbf{X}_{mt}. \tag{2}$$

The intercept α_m captures market-specific profitability. The vectors $\boldsymbol{\alpha}^{\text{startup}}$ and $\boldsymbol{\alpha}^{\text{non-startup}}$ measure how competing projects at each stage change the payoff. Through this payoff, market competition affects both entry and development incentives.

4.4 Startup's Dynamic Problem

We solve the startup's problem backward from development to entry.

4.4.1 Development Stage

An unacquired startup chooses each period whether to pay a development cost and continue its project or to exit with zero payoff. The cost c_y depends on the phase. If the startup continues, a trial result arrives with probability $G_y^{\text{result}}(h_{it})$. Conditional on a result, the trial succeeds with probability $G_{y,m}^{\text{success}}$ and fails otherwise. A failed project exits with zero payoff.

The value of continuing combines the development cost, the value of waiting for a trial result, and the value of success:

$$v_{it}^{D,y}(S_{it}) = -c_y + \Big(1 - G_y^{\text{result}}(h_{it})\Big)\beta\,\mathbb{E}\Big[V_i^S(S_{i,t+1}) \mid S_{it}, y_{i,t+1} = y\Big] + G_y^{\text{result}}(h_{it})\, G_{y,m}^{\text{success}}\, \bar{v}_{it}^{y}(S_{it}). \tag{3}$$

The value of success depends on the phase:

$$\bar{v}_{it}^{y}(S_{it}) = \begin{cases} \beta\,\mathbb{E}\Big[V_i^S(S_{i,t+1}) \mid S_{it}, y_{i,t+1} = 2\Big], & y = 1, \\ \pi_i(S_{it}), & y = 2. \end{cases}$$

Phase I success leads to Phase II in the next period, while Phase II success yields the terminal payoff.

A startup continues development when this value plus a private shock is positive, which yields a logit development choice probability. The shock ε_{it}^D follows a standard logistic distribution with CDF Λ. The development choice probability and the ex ante development value are

$$P_i^{D,y}(S_{it}) = \Lambda\Big(v_{it}^{D,y}(S_{it})\Big), \qquad V_i^D(S_{it}) = \log\Big(1 + \exp(v_{it}^{D,y}(S_{it}))\Big).$$

Acquisition opportunities raise the value of development because the next-period startup

value includes the value of being acquired. The continuation value V_i^S in equation (3) is the startup value before the next acquisition stage. A higher acquisition value therefore raises $v_{it}^{D,y}$ and the probability of continuing. We call this channel innovation for buyout.

4.4.2 Acquisition Stage

Each startup meets one randomly selected non-startup acquirer per period and bargains over an acquisition. Let V_{bit}^B denote the value of the project to acquirer b, net of its disagreement payoff. The startup's disagreement payoff is its development value $V_i^D(S_{it})$, so the deterministic surplus from the deal is $\Delta_{bit} = V_{bit}^B - V_i^D(S_{it})$. The pair agrees to an acquisition when $\Delta_{bit} + \varepsilon_{bit}^A > 0$, where ε_{bit}^A follows a standard logistic distribution. This rule gives the acquisition choice probability $P_{bit}^A(S_{it}) = \Lambda(\Delta_{bit})$. An acquired project leaves the startup population and becomes a non-startup project.

We specify the deterministic acquisition surplus directly as a linear function of covariates, including the project's phase, the market state, and characteristics of the acquirer and the startup:

$$\Delta_{bit} = W_{bit}'\gamma.$$

Nash bargaining with a fixed bargaining weight determines the acquisition price. With startup bargaining weight η, the price solves

$$p_{bit}^* = \arg\max_p \Big(p - V_i^D(S_{it})\Big)^{\eta}\Big(V_{bit}^B + \varepsilon_{bit}^A - p\Big)^{1-\eta} = V_i^D(S_{it}) + \eta\Big(\Delta_{bit} + \varepsilon_{bit}^A\Big). \tag{4}$$

The startup value before bargaining equals the development value plus the expected value of acquisition opportunities:

$$V_i^S(S_{it}) = V_i^D(S_{it}) + \eta\,\mathbb{E}_b\Big[\log\Big(1 + \exp(\Delta_{bit})\Big)\Big]. \tag{5}$$

The expectation is over the randomly selected acquirer. The second term rises with the acquisition surplus and with the startup's bargaining weight.

4.4.3 Entry Stage

A potential entrant enters when the expected startup value of a new Phase I project, net of the entry cost, plus a private shock is positive. The value of entry is

$$v^E(M_{mt}) = -\kappa + \beta\,\mathbb{E}\Big[V_i^S(S_{i,t+1}) \mid M_{mt}, y_{i,t+1} = 1, h_{i,t+1} = 0\Big],$$

where κ is the entry cost. With a standard logistic shock ε_{it}^{E}, the entry choice probability is $P^{E}(M_{mt}) = \Lambda\Big(v^{E}(M_{mt})\Big)$.

Because the startup value includes acquisition opportunities, the prospect of a buyout raises the incentive to enter. An entrant weighs the entry cost against both the development value and the acquisition value of its future project. We call this channel entry for buyout.

4.5 Equilibrium

We focus on Markov perfect equilibria in pure strategies, as in Bajari, Benkard and Levin (2007). In such an equilibrium, each startup's entry, development, and acquisition decisions depend only on its state and private shocks, and they are optimal given the other startups' strategies, which determine how $\mathbf{n}_{mt}^{\text{startup}}$ evolves. As is standard in this literature, we assume that the data are generated by a single equilibrium in each market, so the first-step estimates recover the equilibrium choice probabilities.

4.6 Counterfactuals

We use the estimated model to evaluate policies that restrict acquisitions of startups. We compute counterfactuals that ban acquisitions in a specific phase, such as Phase I or Phase II, and that ban all acquisitions. Comparing these counterfactuals with the baseline measures how acquisitions affect entry for buyout and innovation for buyout.

5 Conclusions

This paper studies how acquisition opportunities affect startup entry and drug development. We combine drug project data with acquisition data to build a panel of 162 therapeutic markets from 1989 to 2015. Reduced-form regressions show that acquisitions are positively correlated with startup entry and early-phase drug development. We then develop a dynamic game of entry, drug development, and acquisition that separates buyout incentives from competitive effects. We build this model to evaluate policies that ban acquisitions in a specific phase or in all phases.

For future work, we plan to do three things. First, we will test whether the reduced-form correlations are causal by using patent cliffs as an instrument variable for acquisitions. Pharmaceutical firms may replenish their portfolios through acquisitions when patents on their existing drugs expire. A firm's scheduled patent expirations can therefore generate exogenous variation in its acquisitions motive. Second, we will extend the structural model to include the acquisition market explicitly. The current model treats acquisitions in a simple

way, but modeling which firms acquire which startups will give a more realistic interpretation of mechanisms. Third, we will estimate the model and use it to carry out the counterfactual policy evaluations.

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