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Competition and the Efficiency of Markets for Technology

Marie-Laure Allain
Department of Economics and National Center for Scientific Research, Ecole Polytechnique, 91128 Palaiseau Cedex, France, marie-laure.allain@polytechnique.edu

Emeric Henry
Sciences Po, 75007 Paris, France; and Centre for Economic and Policy Research, London EC1V 3PZ, United Kingdom, emeric.henry@sciences-po.f

Margaret Kyle
MINES ParisTech (CERNA) and PSL Research University, 75272 Paris Cedex 06, France; and Centre for Economic Policy Research, London EC1V 3PZ, United Kingdom, margaret.kyle@mines-paristech.fr

The sale of ideas through licensing facilitates the division of labor between the separate activities of research and development. This vertical specialization can improve the overall efficiency of the innovative process. However, these gains depend on the timing of the sale: the buyer of an innovative project should assume development at the stage at which he has an efficiency advantage. Using data from the pharmaceutical industry, we show that competition between potential buyers is related to the timing of licensing. Furthermore, the effect differs by the type of competitor. We then describe a class of models that yields predictions consistent with these empirical patterns. Our key insight is that increased competition may increase licensing delays and hence inefficiency.

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1. Introduction

Specialization in different phases of the innovative process is increasingly common in industries such as pharmaceuticals, chemicals, and semiconductors (Arora et al. 2001). This division of labor, facilitated by the growth of licensing markets that allow for the sale of projects, potentially improves the efficiency of the innovative process. We argue in this paper that these efficiency gains crucially depend on the timing of exchange, by which we mean the phase of development at which an innovative project is transferred from one firm to another. Consider two firms, one more efficient in conducting early-stage research (R) and the other more efficient in the final stage of product development (D). It is socially optimal to have the relatively efficient firm own the project at each stage, i.e., to transfer the project to the second firm at the end of the initial stage. A delay in this transfer increases the total cost of innovating and the probability that innovations are abandoned. Thus, the timing of technology transfer is an important determinant of the innovation rate.

We present new empirical evidence from pharmaceutical licensing that suggests a relationship between market structure and delays in the sale of ideas or projects. Next, we build a theoretical model that generates predictions that are consistent with the patterns we observe in the data. Our main focus is the relationship between market structure and the timing of licensing, which has implications for the efficiency of markets for technology, and we identify several market characteristics that can generate this link. In the main model, we consider the case where the seller is more confident than the buyers about the prospects of the project. We then explore other plausible assumptions. For example, the seller might be better informed about the quality of the project or about some characteristic of the market, such as the number of buyers competing for the purchase. The buyer and seller may also have different risk profiles. Any of these assumptions yields the same qualitative result for the relationship between the efficiency markets for technology and competition.

In recent decades, the pharmaceutical industry has seen increasing division of innovative labor between small biotechnology firms and large pharmaceutical companies. For instance, Angell (2004) claims that one-third of the drugs marketed by major pharmaceutical companies originate from licenses with biotechs or universities. Biotechnology companies seem to

have a comparative advantage in achieving early-stage discoveries, whereas large pharmaceutical firms are considered more efficient in conducting later-stage clinical testing. Biotechnology firms may be more confident of, or better informed about, the quality of their drug candidates than potential buyers. Verifiable information is revealed during the clinical trials that are required for regulatory approval. Once a clinical trial phase is successfully completed, the difference in quality beliefs shrinks and the potential buyers of a license become more certain of the drug candidate's value. These clinical phases are subject to regulatory oversight, and this facilitates the identification of the development phase at any point in time for a new drug candidate.

The importance of markets for technology and the availability of data on licensing makes the pharmaceutical industry ideal for a study of licensing delays. We combine data on licensing deals and the stage of drug development at signing with data on downstream competitors, who compete on the product market as well as for the license. Controlling for various measures of financial constraints and other factors, we provide empirical evidence that there is a relationship between competition and licensing delay. Specifically, we show that an increase in the number of buyers has a nonmonotonic effect on licensing delays, and we show that an increase in the number of entrants in the disease market delays licensing, whereas an increase in the number of incumbents reduces delays.

This evidence motivates our theoretical analysis. Our baseline model assumes seller overconfidence, though several other assumptions (discussed below) yield similar predictions. At the start of the first period, an innovator has a project that requires additional development to be brought to market. The innovator does not have the resources necessary to launch the drug, should development be successful, but she can choose to license in the first period or to do so after incurring additional development costs. At least two firms compete on the downstream product market and are potential buyers of the license. Although the innovator faces some positive cost of development, development is costless for the buyers. It is thus socially optimal to transfer the project from the innovator to one of the buyers in the first period. The value of the project is uncertain before development, and the seller is more optimistic: she assigns a higher probability than the buyers do that the project is good. Subsequent development efforts reveal verifiable information that resolves all uncertainty about the project's value.

We identify a necessary and sufficient condition for efficient transfer of the project in the first period. The key trade-off is the following: because the price of the project in the first period incorporates buyers' uncertainty about its quality, the innovator, who is more confident that her project is good, is tempted to wait for information about the project's value to be revealed, at which point she obtains a price that reflects its true quality. However, she must incur development costs to provide such information. An agreement can therefore be reached in the first period only if the efficiency advantage of buyers in the development stage is large compared with the overconfidence difference between the seller and the buyers.

Our primary interest is how market structure affects the efficiency of markets for technology. We find that when profits on the downstream market do not depend on the number of buyers n, an increase in the number of buyers unambiguously delays the transfer. That is, counter to the usual intuition, more competition leads to greater inefficiency in the market for innovative projects. An increase in n increases the price an innovator can expect for the project in the second period if the project is good, because it both increases the bargaining power of the seller and decreases the development cost of the buyer (that is, the lowest draw of costs). Since the innovator is more confident that this is indeed the case, she is therefore more inclined to wait when n is large.

When profits on the downstream market also depend on n, an increase in the number of buyers has two countervailing effects on the second-period price: in addition to the effect on price described above, it also decreases the downstream profits obtained from the innovation. That is, the innovator obtains a larger slice of a smaller pie. In this case, we identify a condition under which increased competition leads to earlier signing.

We also study a variant of the model in which we distinguish two types of potential buyers: incumbents with existing products on the market and potential entrants without any stake. Although additional entrants affect competition for the innovation, the downstream profits an entrant realizes from signing depend only on the number of incumbents. We show theoretically that delay in the transfer is increasing in the number of entrants and typically decreasing in the number of incumbents. This model will be the core of our empirical analysis. As stated earlier, we find similar results for a wide variety of models, which we discuss in §5, with different plausible assumptions.

There is a large literature that examines different aspects of licensing contracts, such as the choice between fixed fees and royalty rates and allocation of control rights, both theoretically and empirically (Lerner and Merges 1998, Lerner and Malmendier 2010, Kamien and Tauman 1986, Beggs 1992, Choi 2001).[1]

[1] See also Anand and Khanna (2000), Vishwasrao (2006), Mendi (2005), and Higgins (2007).

However, with the exception of Gans et al. (2008) and Luo (2014), the timing of licensing has been ignored. Gans et al. (2008) describe several reasons for deviations from the socially optimal timing of technology transfer, including search costs, asymmetry of information, and uncertain property rights. They show that the resolution of uncertainty over the scope of intellectual property (specifically, a clarification of the claims granted to a patent) speeds licensing. Like Luo (2014), we assume a difference in beliefs between buyer and seller as the key friction in the market for projects, but we focus on the impact of market structure on timing.

Assuming asymmetric information between the seller and buyers leads to similar results. Much of the existing literature on technology transfers under asymmetric information focuses on the case of weak or nonexistent intellectual property rights. In particular, Anton and Yao (2002) examine the problem of an innovator revealing some information to convince a potential buyer of the quality of her product under the risk that the buyer can then fully appropriate the invention without any form of payments. We concentrate here on a different aspect. Property rights do exist, but to convince a buyer of the project's value, the innovator is forced to incur development costs even when she has no comparative advantage in development.

The structure of this paper is somewhat unorthodox, because we present empirical results before the theoretical model. We begin in §2 by describing the data and estimation approach used to establish a link between market structure and licensing delays, with the results in §2.3 through Appendix B. In §3 we introduce a baseline theoretical model. In §4 we present the results on the timing of the transfer and discuss the effect of market structure. In §5, we show that a large class of models leads to the same qualitative results. All the proofs can be found in the appendix.

2. Empirical Evidence on the Link Between Market Structure and Timing

Our goal in this section is to establish several empirical patterns in a setting where markets for technology are important and well developed. First, the timing of licensing displays considerable heterogeneity. Some of this variation is explained, quite intuitively, by factors related to an observable quality of innovators and their financial conditions. However, we also demonstrate that the timing of licensing is related to the number of potential buyers of a license. We use the existence of this link to motivate a theoretical model that yields predictions consistent with the empirical evidence we describe.

2.1. Background on the Pharmaceutical Industry

Drug development involves several distinct phases that are clearly defined and controlled by regulatory agencies such as the Food and Drug Administration in the United States or the European Medicines Agency. During the discovery phase, firms identify drug candidates for further development in targeting a disease or indication. These are tested in animal subjects during the preclinical phase. At this point, clinical trials in humans begin. Phase I trials involve a small number of healthy volunteers to establish a drug candidate's safety. Phase II trials focus on the efficacy of the drug candidate in treating patients with the disease and begin to identify side effects. Phase III trials are much larger studies that continue to gather data on safety and efficacy. They are typically conducted in many different sites across several countries, requiring significant coordination and expertise. Verifiable evidence of a drug candidate's quality is produced at each phase and presented to the regulatory agencies.

Markets for technology play an increasingly important role in the pharmaceutical sector. In a 2006 survey of innovation, the *Economist* notes that "Big Pharma's R&D activity is now concentrated as much on identifying and doing deals with small, innovative firms as it is on trying to discover its own blockbuster drugs" (*Economist* 2006). Biotechnology companies seem to have a comparative advantage in early-stage discovery, whereas large pharmaceutical firms are considered more efficient in conducting later-stage clinical testing. For example, they can exploit their relationships with medical practitioners who participate in running clinical trials or prescribe their other products. Large pharmaceutical firms also may benefit from economies of scale and scope in the administration of clinical trials. Inexperienced biotech firms may have trouble designing clinical trials or interpreting their clinical data, requiring additional trials. Drug candidates are usually sold with exclusive licensing contracts.[2]

Though the idea that entrepreneurs or innovators are overoptimistic has received more theoretical attention than empirical study, we have some justification for this assumption in our setting. Lowe and Ziedonis (2006) found evidence consistent with entrepreneurial overconfidence in a study of university technology transfer; in particular, entrepreneurs in their sample were more likely to pursue failed development efforts than were more established firms. In a study of cancer drug candidates, Guedj and Scharfstein (2004) show that smaller biotech firms are more likely to advance their projects from Phase I to Phase II than larger or

[2] Even though direct acquisitions of the company also occur, we will focus on the empirical analysis on the licensing channel.

more experienced firms but see higher failure rates later on. The authors interpret this pattern as evidence of an agency problem between managers and shareholders, but overconfidence on the part of either would yield the same result.

2.2. Data

We draw our sample of licensing contracts from Recombinant Capital's recombinant DNA (rDNA) database. It contains detailed information on all licensing deals in the pharmaceutical industry signed since 1973, including financial details (total value, up-front and milestone payments, royalty rates) for a subset of the agreements. It also provides information about the geographical region covered by the license and about the type of contract (marketing, production, research). Finally, it records the phase of development of the drug at the time the license was signed.

Our sample, by construction, includes only licensed projects. That is, we do not consider the choice of vertical integration versus licensing, only the timing of a license conditional on the signing of a contract. For small biotech firms, it is very rare to observe projects developed without assistance from another firm at some point. In other words, we take it as given that a small firm must license, and we focus on when. Our estimated coefficients should be interpreted as applicable only to this subset. In addition, we assume that failure rates in each phase are independent of the number of competitors. Although evidence suggests that failure rates may differ systematically across firm types, we think it is reasonable to believe that results from clinical trials at each phase are not directly related to the number of downstream competitors.

We are interested in how downstream market structure affects licensing, so we need to define a downstream market and the number of potential licensees of an innovation. Since the rDNA database contains no information on potential licensees or any other market-level data, we exploit additional data sources called R&D Focus and MIDAS, both from IMS Health. MIDAS provides us with annual data on total revenues by disease from 15 countries from 1993 to 2007. The R&D Focus database tracks all drug candidates, or projects, in development since the early 1990s. This source allows us to create measures of each firm's experience in drug development as well as in marketing approved products at the disease level.

We used a number of standard sources for firm-level information, such as VentureXpert, Compustat, Osiris, and CorpTech. We identify whether each firm is publicly traded or privately held and collect some financial data, where possible, such as the amount of venture capital financing. Because many of the firms in our study are privately held and roughly half are headquartered outside of the United States, our financial information is somewhat limited.

We restrict our analysis to contracts involving R&D on drug candidates that have not yet been approved for launch, excluding comarketing alliances. We focus on exclusive deals with no geographic restriction and on deals that are signed in the discovery, preclinical, or clinical phases of development. To match each deal to market-level variables for which we have data, we include deals from 1990 to 2007. These exclusions reduce our sample of interest to 6,426 (including observations for which the stage at signing is missing) from a total of 14,976 deals in recombinant capital. In practice, this requires us to match each licensing agreement from the rDNA database with a project in the R&D Focus database by hand, using information on the partnering firms and the subject of the license. In addition, we concentrate on deals that involve a specific drug candidate (or candidates, in some cases) rather than those for the use of a technology platform (which are rarely exclusive agreements). This process results in 2,335 matches. We have the least success in matching very-early-stage deals and those where the stage at signing is missing in the rDNA database.

Important for our definitions of potential buyer and downstream market is a drug's Anatomical Therapeutic Chemical classification (hereafter, therapeutic class).[3] Therapeutic classes correspond to disease markets and are coded at different levels of specificity. For example, the broadest level is a single letter, such as group C for cardiovascular system therapies. C02 refers to the subgroup of antihypertensive therapies, and C02A is the narrower set of centrally acting antiadrenergic agents. Drugs within a therapeutic class may be considered substitutes, but drugs within the same narrow class are closer substitutes than those in the same broad class. Substitution is unlikely across therapeutic classes. For example, the market for antiacne preparations (D10) is separate from that of drugs used for diabetes (A10), and human insulins (A10A) are closer substitutes than oral antidiabetics (A10B) in the treatment of diabetes. We exclude the therapeutic class V07 (defined as "all other non-therapeutic products") because the set of products assigned to this class are not substitutes for each other.

[3] The World Health Organization describes this classification scheme as follows: "In the Anatomical Therapeutic Chemical (ATC) classification system, the active substances are divided into different groups according to the organ or system on which they act and their therapeutic, pharmacological and chemical properties. Drugs are classified in groups at five different levels. The drugs are divided into fourteen main groups (1st level), with one pharmacological/therapeutic subgroup (2nd level). The 3rd and 4th levels are chemical/pharmacological/therapeutic subgroups and the 5th level is the chemical substance. The 2nd, 3rd and 4th levels are often used to identify pharmacological subgroups when that is considered more appropriate than therapeutic or chemical subgroups" (http://www.whocc.no/atc/structure_and_principles/, accessed September 26, 2015).

Table 1 Summary Statistics

Variable	*N*	Mean	SD	Min	Max
Late signing (*post-preclinical*)	2,066	0.29	0.45	0.0	1.0
log(*months since start of preclinical*)	1,814	1.12	1.82	0.0	5.6
Licensor market experience (*no. drugs marketed*)	2,047	3.20	13.65	0.0	198.0
Licensor development experience (*no. drugs in development*)	2,047	6.38	16.44	0.0	302.0
Licensor deal experience (*no. deals previously signed*)	2,047	1.49	2.47	0.0	17.0
Licensor is publicly traded	2,066	0.15	0.36	0.0	1.0
Licensor is based outside the United States	2,066	0.42	0.49	0.0	1.0
Firms are colocated (*same country of headquarters*)	2,066	0.42	0.49	0.0	1.0
Licensor is not in VentureXpert data	2,047	0.49	0.50	0.0	1.0
Licensor's round of venture financing	1,026	3.69	2.68	1.0	20.0
Licensor's funding in last round of venture financing	1,026	10.90	18.65	0.0	150.0
Licensor's cumulative venture financing	1,026	28.52	33.11	0.0	244.6
Licensor's age	1,048	8.23	5.60	0.0	20.0
Total revenues in therapeutic class (*millions of US*$)	1,672	4.27	4.77	0.0	30.6
Total venture funding for industry (*units of US*$)	2,065	9.15	4.23	0.0	16.7
Potential buyers	2,047	42.40	27.73	0.0	113.0
Incumbents that sign at least one license	2,047	22.78	19.95	0.0	80.0
Entrants that sign at least one license	2,047	19.62	15.06	0.0	94.0
Incumbents, all firm types	2,047	63.51	59.09	0.0	243.0
Entrants, all firm types	2,047	35.92	33.87	0.0	230.0
Incumbents that are large and public	2,047	8.13	5.09	0.0	20.0
Entrants that are large and public	2,047	7.67	5.35	0.0	24.0

Drug candidates are often assigned to multiple therapeutic classes because they can treat different diseases. In addition, most drug candidates have more than one firm listed as codeveloper. When counting the number of firms active in a therapeutic class, we consider all firms that are involved in the development of a project, and we include all projects that are assigned to the therapeutic class. Thus, our measures of the number of firms in a therapeutic class are very inclusive. This is largely because of the difficulty in determining which firms did what (developed at what stage, marketed in which countries or for which disease, etc.), based on the information included in R&D Focus.

Table 1 provides summary statistics for the key variables in our analysis. We examine only drug candidates that were licensed between 1990 and 2007, not the set of all drug candidates that were ever (or are currently) available for licensing. Our estimates therefore apply only to a selected sample. All variables are measured as of the date a license was signed. The definitions of incumbents and entrants are described in Appendix B.

2.3. Distribution of License Timing

We first demonstrate that there is variation in when new technologies or drug development projects are transferred from innovators to downstream firms, and that the distribution has changed over time. Figure 1 illustrates that the fraction of licensing contracts signed after the discovery and preclinical stages has increased by more than 30% since 1990. It is worth noting that since the mid-1990s, relatively few new drugs have been launched. Many explanations exist for this decline (Cockburn 2007b), but one unexplored hypothesis is that delays in technology transfer are associated with lower productivity or efficiency. In addition, the shift in the distribution of the timing of licenses coincides with a period of increased market concentration, as the pharmaceutical industry has undergone substantial consolidation. For example, Sanofi today is the combination of Synthélabo, Rhône-Poulenc, Hoechst, and Genzyme. Pfizer has merged with Warner-Lambert, Pharmacia,

Figure 1 (Color online) Stage at Licensing Signing Over Time

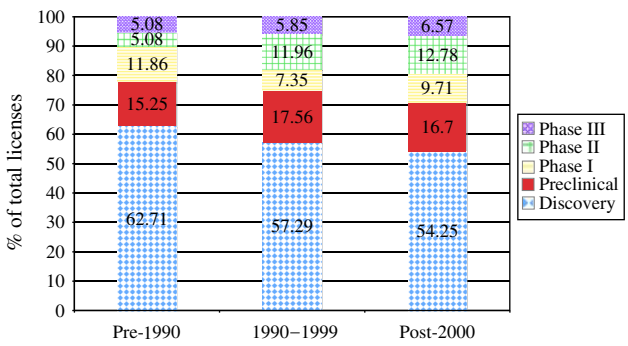


Table 2 Percentage of License Stage by Quartile of Competition

	Quartile of competition			
Stage	1	2	3	4
Early	79.20	68.55	72.61	70.83
Late	20.80	31.45	27.39	29.17

and Wyeth. Merck acquired Schering-Plough, and Astellas is the result of a merger between Yamanouchi Pharmaceutical and Fujisawa Pharmaceutical. Some analysts noted the potential consequences of these mergers for smaller biotechnology firms (Fletcher 2002). This justifies our particular focus on the link between market structure—specifically the number of potential buyers—and the timing of technology transfer.

2.4. Timing and the Number of Competitors

To begin, we show a simple breakdown of the distribution of early- versus late-stage licensing by quartile of competition in Table 2. Specifically, competition refers to the number of potential buyers of a license, which we discuss in greater detail below, and late-stage licensing refers to Phase I, II, or III of clinical development. " As is evident from Figure 1, there are far more early-stage licenses than late-stage overall; there are far fewer drug candidates in later phases of development because of high failure rates. However, there are relatively more late-stage licenses signed when competition is greatest (quartile 4 in Table 2) than when there are few potential buyers (quartile 1). The relationship between late-stage licensing and competition does not appear to be monotonic. We now examine in the regression analysis that follows whether this relationship is still present when controlling for various factors influencing the decision to license.

We exploit variation in the number of competitors across therapeutic classes, and within therapeutic classes at different points in time, to identify the effect of market structure. Naturally, any regression in which competition appears as an explanatory variable raises concerns about endogeneity. Given the entry barriers and lengthy development times required, the number of competitors in a market is largely fixed in the short run; new entry reflects business decisions taken years before, rather than an endogenous response to early- or late-stage licensing. The number of competitors also changes if a merger takes place, but it seems unlikely that mergers between large firms are motivated by the timing of license contracts. Our main concern is the existence of an omitted variable that is correlated with differences in competition between therapeutic classes and with the timing of licensing, which is testable only with a potential instrument for competition. Although it is not clear what such an omitted variable might be (additional controls are discussed below), we lack good candidates to instrument for the number of competitors. No major regulatory change affecting competition occurred during our sample period, and we have no geographic variation in competition. Therefore, we make no claims regarding causality.

We use three empirical methods: logit, ordered logit, and a hazard rate model. The first approach defines an "early" stage of licensing (the discovery and preclinical phases) and a "late" stage (Phases I, II, and III trials). Testing involving human subjects is more expensive and requires more complicated study design, and it is during these phases of development that large, experienced firms probably have a comparative advantage. An alternative is to treat each of these distinct phases as a "period" and assume that a similar trade-off exists between signing in stage i and delaying until stage $i+1$ for each stage i. Two natural empirical models are the logit (for early versus late) and ordered logit (for each phase of development). Our latent regression is

$$y^* = \beta N + \gamma X + \epsilon,$$

where N is a vector of competition measures and X is a vector of controls, described below.

Another approach, similar to that taken by Gans et al. (2008), is a hazard model in which a biotechnology firm's innovation is "at risk" for licensing from the time the drug candidate reaches the preclinical stage of development. We examine what factors affect the hazard rate of the drug candidate's transfer to a licensee. Since censoring is not an issue in our data, we take the simplest approach and regress the natural log of the months since a drug candidate entered the preclinical phase on the same variables as used in the ordered logit. There is considerable heterogeneity in the time required to complete clinical trials; drugs for chronic conditions may require longer trials than those for acute conditions, for example, and a hazard model may confound the complexity of trials with the strategic delay that is our interest.

The main challenge we face for our empirical exercise is to define a potential buyer. We argue that firms with product market experience in the same disease area as the drug candidate for license are the most likely buyers. Such firms have a good understanding of the market potential and are able to evaluate the scientific validity of a drug candidate available for license. In addition, these firms have preexisting relationships with doctors who treat the disease and who may enroll patients in clinical trials as well as prescribe the drug once it is approved. In other words, these firms should have relatively lower costs of conducting clinical trials and marketing the product and

the highest expected profits from signing a license. We restrict the set of potential licensees of a drug candidate to firms with existing products in the same broad disease area, or two-digit ATC code, as the drug candidate licensed. For our baseline results, we focus on those firms that buy at least one license; this essentially means that we do not consider firms that mostly sell drug candidates (usually small biotechs) as potential buyers of other drug candidates. Any definition of potential licensee risks excluding some actual buyers and/or including some that are not true competitors for the license. We therefore repeat the analysis using different definitions of potential buyers, and these results are presented in Appendix B.

Although the relationship between timing and competition is our main focus, we include a number of controls that the existing literature suggests should affect licensing behavior. These include the extent to which a licensor faces capital constraints and various other factors such as experience in licensing (measured as the number of previous licenses the biotech firm has granted), experience in drug development (measured as the number of drug candidates the licensing firm has previously initiated), and market experience (measured as the number of drugs the licensing firm has successfully launched). Because the availability of financing may vary over time, we also include annual commitments by venture capitalists within the biotechnology and medical industries. All specifications also include therapeutic class fixed effects, to control for differences in demand as well as development costs or risks that are likely to vary by disease, and a control for the size of the therapeutic class market, measured as total annual revenues from 15 countries for drugs assigned to that therapeutic class. Standard errors are clustered by disease in all models reported here.

Table 3 presents our baseline results for the three econometric models described above. Competition appears to have an inverted U-shaped effect on the timing of licensing. This effect is illustrated in Figure 2, which graphs the predicted probability of late signing (using the estimates of the logit model over the range of values observed in our data set) as the number of buyers changes with continuous variables at their means for a U.S.-based licensor that is not publicly traded. The mean number of buyers using our very inclusive definition is 42, and the peak of the inverted U is approximately 55.[4]

[4] We also experimented with market concentration (measured as the Herfindahl-Hirschman Index) rather than a count of the number of buyers. However, this measure has less variation across disease if we calculate market shares based on global sales, since not all drugs are launched in all markets. This lack of variation makes it difficult to achieve statistical significance.

Table 3 Baseline Results

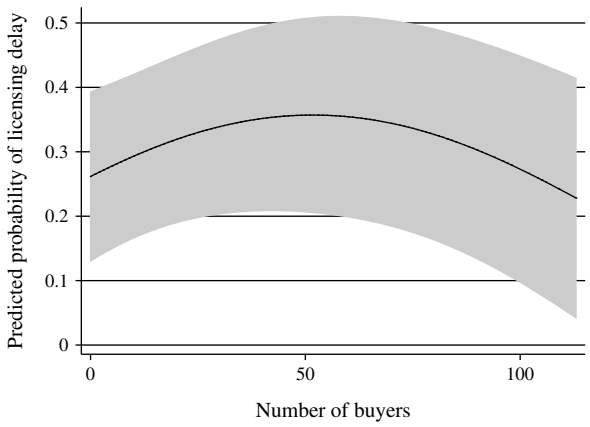
Variable	Logit	Ordered logit	Hazard rate
Intercept	−2.2233**	−1.6605**	−0.1384
	(0.5437)	(0.4523)	(0.4369)
Potential buyers	0.0161*	0.0140*	0.0240**
	(0.0097)	(0.0080)	(0.0080)
Buyers squared	−0.0002**	−0.0002**	−0.0002**
	(0.0000)	(0.0000)	(0.0001)
Total venture funding for industry	0.0225	0.0429**	0.0476**
	(0.0219)	(0.0184)	(0.0186)
Total revenues in therapeutic class	0.0363**	0.0327**	0.0161
	(0.0138)	(0.0119)	(0.0124)
Licensor market experience	0.0076	−0.0015	0.0115
	(0.0108)	(0.0096)	(0.0096)
Licensor development experience	−0.0047	0.0059	−0.0118
	(0.0107)	(0.0095)	(0.0095)
Licensor deal experience	−0.0193	−0.0471**	−0.0057
	(0.0235)	(0.0203)	(0.0205)
Licensor is publicly traded	0.5088**	0.4202**	0.6539**
	(0.1776)	(0.1537)	(0.1562)
Licensor is based outside the United States	0.0530	0.1234	−0.0053
	(0.1286)	(0.1086)	(0.1094)
Firms are colocated	−0.5903**	−0.4604**	−0.4542**
	(0.1282)	(0.1066)	(0.1050)
Licensor is not in VentureXpert data	0.4952**	0.5358**	0.4344**
	(0.2068)	(0.1730)	(0.1675)
Licensor's cumulative venture financing	0.0046	0.0053*	−0.0023
	(0.0035)	(0.0030)	(0.0032)
Licensor's funding in last round of venture financing	−0.0097	−0.0106**	0.0042
	(0.0059)	(0.0051)	(0.0050)
Licensor's round of venture financing	−0.0226	−0.0185	0.0306
	(0.0382)	(0.0331)	(0.0326)
Licensor's age	0.0711**	0.0712**	0.0792**
	(0.0157)	(0.0134)	(0.0139)
Number of obs.	1,633	1,633	1,449
Log L or R^2	−935.4465	−2,084.579	0.085

Note. L, likelihood.
* and ** denote significance at the 10% and 5% levels, respectively.

2.5. Timing and the Type of Competitor

Potential buyers of a license may not be equally exposed to downstream competition and its countervailing effect on licensing delay. Firms that market

Figure 2 Effect of Competition on the Probability of Late Signature



a product in the same narrow disease area are most affected by downstream competition, whereas those that are active in related diseases are less so. We refer to the former as incumbents in the market and the latter as potential entrants.

We define incumbents as firms with drugs in the same three-digit ATC code as the licensed drug; entrants are firms with drugs in the same two-digit ATC code as the licensed drug but not in the same three-digit ATC code. Both definitions include only firms that buy at least one license in our data. The results are presented in Table 4; the specifications include all the additional explanatory variables as in our baseline case, but we report only the coefficients for incumbents and entrants. Across all specifications, the predictions of our theoretical model are confirmed: an increase in the number of incumbents (respectively, entrants) decreases (respectively, increases) licensing delays. To assess the importance of the effect of competition, we calculate the average elasticity of the probability of late signing with respect to incumbents and entrants. The percentage change in the probability of late signing for a 1% change in the number of incumbents is −0.31, and the corresponding figure for entrants is 0.17. We explore the robustness of these results in Appendix B using different definitions of entrants and incumbents. We confirm the negative and significant effect of incumbents and the positive effect of entrants.

Table 4 Results with Incumbents and Entrants

Variable	Logit	Ordered logit	Hazard rate
Intercept	−1.9810**	−1.4105**	0.1789
	(0.5126)	(0.4255)	(0.4054)
Incumbents	−0.0169**	−0.0232**	−0.0116**
	(0.0050)	(0.0042)	(0.0042)
Entrants	0.0113**	0.0080**	0.0145**
	(0.0041)	(0.0034)	(0.0035)
Total venture funding for industry	0.0194	0.0395**	0.0431**
	(0.0218)	(0.0183)	(0.0183)
Total revenues in therapeutic class	0.0572**	0.0554**	0.0320**
	(0.0147)	(0.0127)	(0.0129)
Licensor market experience	0.0063	−0.0029	0.0114
	(0.0108)	(0.0096)	(0.0096)
Licensor development experience	−0.0037	0.0071	−0.0118
	(0.0107)	(0.0095)	(0.0095)
Licensor deal experience	−0.0141	−0.0419**	−0.0029
	(0.0236)	(0.0204)	(0.0203)
Licensor is publicly traded	0.5598**	0.4871**	0.6930**
	(0.1785)	(0.1538)	(0.1549)
Licensor is based outside the United States	0.0774	0.1635	0.0160
	(0.1294)	(0.1092)	(0.1089)
Firms are colocated	−0.5788**	−0.4475**	−0.4403**
	(0.1289)	(0.1070)	(0.1045)
Licensor is not in VentureXpert data	0.4510**	0.5050**	0.4134**
	(0.2077)	(0.1733)	(0.1665)
Licensor's cumulative venture financing	0.0042	0.0050*	−0.0025
	(0.0035)	(0.0030)	(0.0031)
Licensor's funding in last round of venture financing	−0.0095	−0.0102**	0.0045
	(0.0060)	(0.0051)	(0.0049)
Licensor's round of venture financing	−0.0153	−0.0077	0.0387
	(0.0385)	(0.0332)	(0.0325)
Licensor's age	0.0697**	0.0710**	0.0785**
	(0.0157)	(0.0134)	(0.0138)
Number of obs.	1,633	1,633	1,449
Log L or R^2	−926.4657	−2,069.873	0.095

Note. L, likelihood.
* and ** denote significance at the 10% and 5% levels, respectively.

To summarize, we find evidence that licensing delays are related to the number of potential buyers and that the effect differs by the type of potential buyer. More specifically, the empirical study establishes three patterns shown in the data on the relationship between competition and the timing of licensing:

1. An increase in the number of buyers has a nonmonotonic effect on licensing delays.

2. An increase in the number of entrants delays licensing.

3. An increase in the number of incumbents reduces licensing delays.

These relationships are robust to including controls for other factors that one would expect to affect the timing of licensing, as well as to small changes in the definition of potential buyers. Our task now is to provide a theoretical explanation for this relationship.

3. Theoretical Model

Based on the findings described above, we now develop a class of theoretical models that link market structure and the timing of licensing. We first provide a detailed description of a model assuming that the seller is overconfident. We then discuss what alternative assumptions yield similar predictions, and we define a common thread for those models that predict the patterns highlighted in the empirical study.

Our model has one innovator with a preexisting project, i.e., one for which initial development costs are sunk.[5] The innovator may sell the project to one of $n \geq 2$ potential buyers. For simplicity, we assume that these firms do not engage in early-stage innovation. The project is sold by running an auction, which we describe below. We consider only exclusive transfers

[5] We consider competition between innovators in Appendix A. We show that the effect of competition between innovators is ambiguous, and therefore we focus here instead on the impact of competition between the buyers.

that grant the full ownership of the innovation to the buyer.

The model has two periods with two key differences. At the end of period 1, if the innovator has not sold the innovation, she needs to decide whether to develop the project further. Development of the innovation from period 1 to period 2 costs Δ for the innovator and 0 for the buyers: we assume potential buyers are more efficient in development. Second, period 1 is characterized by uncertainty about the value of the innovation. The innovator believes the product is good with probability p, whereas the potential buyers believe it is good with probability q. We assume that the innovator is overconfident about the value of the innovation; i.e., $p > q$ (see Hayward et al. 2006, Galasso and Simcoe 2011, Malmendier and Tate 2005 for a discussion of overconfidence). If the innovator chooses to pursue development, the value of the innovation is revealed as a result of the verifiable evidence generated during the development process at the beginning of period 2.

If the project is bad, we assume that it does not generate any profits. If the project is good

- the profit of a buyer is $\pi_0(n)$ if neither he nor any of his competitors sign a license;
- the profit of a buyer is $\pi_l(n)$ if one of his competitors signs a license;
- the profit a buyer is $\pi(n)$ if he signs a license.

We assume $\pi(n) \geq \pi_0(n) \geq \pi_l(n) > 0$. Each buyer wants to buy a good project, but should he fail to do so, he prefers that no rival buys it either. We assume that all profit functions are weakly decreasing in n and are continuously differentiable.

Buyers are heterogeneous. There is a fixed cost of production c that is drawn for each buyer from a uniform distribution with support $[0, \bar{c}]$. The fixed cost must be incurred after observing the value of the invention (it will be paid only if the project is good). Specifically, the value to a buyer of a bad project is 0 but $\pi(n) - c$ if the project is good.

The project is sold through a second-price auction.[6] The seller initially decides whether to run the auction in period 1 or to pay the development cost Δ and wait for the second period to conduct the auction. Note that Δ must be paid before the innovator learns the type of the project.

4. The Timing of the Sale of a Project

In our model, it is socially optimal to transfer the project from the innovator to the buyer in the first period because development is costless for buyers. We show that overconfidence on the innovator's side can systematically delay the sale. Furthermore, market structure affects the timing of the transfer.

4.1. Equilibrium Strategies

We start by characterizing the equilibrium strategies. We first show that the unique bidding strategy for the buyers in both periods is to bid their expected value for the good, a standard result in second-price auctions.

Lemma 1. *In the second period, if the innovation is good, buyer i with cost c_i bids $\pi(n) - \pi_l(n) - c_i$. In the first period, if an auction is run, buyer i with cost c_i bids $q(\pi(n) - \pi_l(n) - c_i)$.*

Using the result of Lemma 1, we can derive the payoff the innovator can expect from running an auction in the first or second period. If she runs it in the first period, she expects a payoff equal to the expected value of the second-highest bid:

$$q\big(\pi(n) - \pi_l(n) - E[c_{n2}]\big), \tag{1}$$

where $E[c_{n2}]$ is the expected value of the second-lowest cost among the costs of the n bidders.

If she waits for the second period (and thus pays the development cost Δ), she expects a payoff of

$$p\big(\pi(n) - \pi_l(n) - E[c_{n2}]\big) - \Delta. \tag{2}$$

This naturally leads to our first result.

Proposition 1. *The unique subgame perfect equilibrium is such that the project is sold in the first period if and only if*

$$\Delta \geq (p - q)\big(\pi(n) - \pi_l(n) - E[c_{n2}]\big). \tag{3}$$

As overconfidence $p - q$ grows, it becomes more likely that the license is signed in the second period.

If this condition is satisfied, the socially optimal timing of licensing is achieved: the project is sold in the first period and the more efficient buyer develops the innovation. However, if the innovator is much more confident than the buyers of the prospects for the project or if the efficiency difference Δ between the innovator and the buyers is small, the threshold for early signature is more difficult to meet and late (and inefficient) signature is more likely. The condition of Proposition 1 can be reexpressed as follows: a license is signed in the first period if and only if the cost of development for the innovator is sufficiently large: $\Delta \geq \underline{\Delta}(n)$, where

$$\underline{\Delta}(n) \equiv (p - q)\big(\pi(n) - \pi_l(n) - E[c_{n2}]\big). \tag{4}$$

In practice, deals vary in terms of the efficiency difference between buyer and seller, as well as differences in their beliefs about the quality of the project.

[6] We do not allow for the possibility for the seller to include a reserve price. This would not affect the main results in our baseline model but could in the case of asymmetry of information, since it can signal the seller's private information.

Some deals will satisfy the condition and reach an early agreement, whereas others will result in an inefficient delay. This trade-off is only relevant in practice if we are in the parameter space where Δ is close to $\underline{\Delta}(n)$, i.e., where the efficiency difference is not quite large enough to meet the condition for early licensing but large enough to be important in terms of welfare loss.

4.2. The Effect of Market Structure

We now investigate how the number of buyers in the market n affects the condition of Proposition 1 and thus the timing of licensing. Specifically, we examine how $\underline{\Delta}(n)$, which we call the efficiency threshold, varies with n. If $\underline{\Delta}(n)$ increases with n, delays in licensing become more likely as the number of competitors increases.

4.2.1. Profits Do Not Depend on n. The number of buyers may influence not only the likelihood that each individual player wins the auction (it directly changes the number of bidders) but also the downstream profits. As a benchmark, we begin with the case where the profits (π_1, π_0, π) do not depend on n. For example, an additional competitor may not affect profits if innovations are purely market expanding and have no business stealing effect. This case isolates the effect of n, the number of firms competing for the license, on the price the innovator can extract. The following proposition states that the effect of n on the timing of licensing is unambiguous in this case.

Proposition 2. *If the payoffs on the market do not depend on n, the efficiency threshold increases with n: the condition for early licensing is harder to meet as the number of buyers increases.*

This result is intuitive. As n increases, the price the innovator can obtain in the auction increases. Indeed, the expected value of the second-lowest cost $E[c_{n2}]$ decreases mechanically as more draws are taken from the distribution. Because of her overconfidence, the innovator perceives higher benefits from waiting, whereas the cost Δ remains unchanged. Thus, overall, an increase in n will delay signature.

Note that the mechanism hinges on the effect of competition between the buyers on the price of the license. Conventional wisdom suggests that the equilibrium price increases with the number of buyers, to reflect competition in an oligopsony. Our auction model has this property, as does a model of sequential bargaining, and we show in Allain et al. (2013) that it yields similar results. If the number of buyers had no effect on the price of the auction, then n would not influence the bargaining power of the innovator, who would extract the full surplus regardless of n. Some auction models even highlight the opposite feature. Bulow and Klemperer (2002) describe situations (which they label "anomalies") where the price of an asset decreases in the number of buyers, as, for instance, in a common value auction with private information. In that case, winners bid more conservatively the more bidders there are, because the winner's curse is worse. Such a feature would reverse our results.[7]

4.2.2. Profits Depend on n. When the profits depend on n, the effect of a change in the number of competitors is more subtle. There are two countervailing effects of n on the price the innovator can extract. On the one hand, it raises the bargaining power of the innovator since there is a higher chance that one bidder has a low implementation cost c. On the other hand, it decreases the actual profits derived from the innovation, since profits are a decreasing function of n. The tension between these two effects yields an ambiguous effect of n on the price in the auction and thus on the timing of licensing.

To obtain precise predictions, we must impose more structure. We assume that profits decrease with n and are positive, a natural assumption in most models of competition. We then obtain the following result.

Proposition 3. *If $\pi'(n) - \pi_l'(n) < -2\bar{c}/(n+1)^2$, then the efficiency threshold decreases in n: the condition for early licensing is easier to meet as the number of buyers increases.*

The intuition of this result is the following. There are now two effects of an increase in n. First, the value of the second-highest bid increases because $E[c_{n2}]$ decreases as more draws of c_i are taken. Given our assumption that the costs are uniformly distributed, the speed at which $E[c_{n2}]$ decreases is given by $2\bar{c}/(n+1)^2$. Second, the profits that the bidders expect decrease with n at a rate $\pi'(n) - \pi_l'(n)$, and so the expected profits decrease for the seller as well. If the second effect dominates, early licensing becomes more likely, since the seller has less incentive to wait. We show in Appendix A that this condition is satisfied for a standard model of Bertrand competition with product differentiation where the innovator introduces a new variety of product on the market.

4.2.3. Entrants and Incumbents. Our previous analysis assumed that all potential buyers were identical except in their implementation cost. In reality, of course, the value of the project may differ across buyers for many other reasons. In this section, we

[7] Although we do not explicitly consider intellectual property rights (IPRs), the conditions of this section are more likely to hold when IPRs are weak. Weak property rights reduce the sensitivity of downstream profits to n, since another class of competitors (imitators) will also be able to enter.

allow for an additional source of buyer heterogeneity, focusing on what we view as a key difference between them: some potential buyers are active in the same class as the licensed innovation, whereas others are not. Formally, we assume that there are n "incumbents," denoted by $i \in \{1, \ldots, n\}$, and e potential "entrants," denoted by $j \in \{1, \ldots, e\}$. Each entrant has a fixed cost of production drawn from the same distribution as the incumbents' costs and the same prior beliefs about the quality of the project. Entrants are not currently active on the downstream market and get profits $\pi_e(n+1)$ (which depend on n, but not on e) from buying the drug. Since they have no current stake on the market, they receive 0 if they fail to buy it. By contrast, an incumbent receives $\pi(n)$ if he buys the license, $\pi_l(n+1)$ if an entrant does, and $\pi_l(n)$ if another incumbent buys the license. In this context, we obtain the following result.

Proposition 4. *All perfect Bayesian Nash equilibria in pure strategies have the following properties*:

1. *The efficiency threshold weakly increases with the number of entrants e: the condition for early licensing is more difficult to meet.*

2. *If $\pi_e(n+1) - \bar{c} \geq \pi(n) - \pi_l(n+1)$, the efficiency threshold decreases with n: the condition for early signing is easier to meet.*

Proposition 4 puts together the two cases discussed in §§4.2.1 and 4.2.2, and it is the core of our empirical analysis. The first result states that an increase in e unambiguously delays licensing. This is in essence a reformulation of Proposition 2. An increase in e has no effect on the profits of the winner but has a direct positive effect on the winning bid since it increases the number of bidders and means that more draws from the cost distribution are taken.

The second result corresponds to the case considered in §4.2.2, since n affects both the number of bidders and the expected profits on the market. The condition $\pi_e(n+1) - \bar{c} \geq \pi(n) - \pi_l(n+1)$ guarantees that an entrant necessarily wins the auction[8] and therefore implies that the only effect of n is to decrease the profits on the market. Note that we can impose a weaker condition (in the spirit of Proposition 3, for instance), but this formulation clearly highlights the main forces at play.

We conclude this section by noting that one obvious solution to the issue of inefficient timing of the transfer of a project is to sign the contract in the first period based on a milestone payment that will be paid if and only if the project turns out to be good. In this environment, without any kind of friction, the project should always be transferred in the first period. However, less than 30% of the subset of licenses signed between 1990 and 2011 for which we have some information on contract details included milestone payments. Over time, this share has been relatively stable.

One natural explanation for the fact that milestone payment contracts are not widely used is moral hazard. It is not possible to contract on everything: in the case of pharmaceuticals, it may be possible to contract on the results of the clinical trials but not necessarily on other dimensions, such as development or marketing efforts. In such situations, the seller might still prefer to wait if he believes the buyers will not exert adequate effort.

5. A Robust Effect of the Number of Buyers

Three key predictions emerged from our theoretical analysis.

1. The number of potential buyers has two countervailing effects on licensing delay (Propositions 2 and 3).

2. Licensing delay increases with the number of entrants (Proposition 4).

3. The delay is likely to decrease with the number of incumbents (Proposition 4).

If there is an efficiency difference between the buyers and seller, then any delay is inefficient.

In this section, we first establish that there is a class of different models that can deliver these predictions. These models share a common structure: there is some imperfect information in period 1, all uncertainty is resolved in period 2, and the buyers are more efficient in development. We next show that there are alternative plausible explanations for the delay in licensing, but they typically appear to be incompatible with the second and third predictions above.

5.1. The Common Thread

We consider a series of different models, some based on asymmetric information between the seller and the buyers and others on differences in risk profiles, that reach the same conclusion as our benchmark model: a sale occurs in the first period if and only if $\Delta \geq \alpha r_2(n)$, where

$$r_2(n) \equiv \pi(n) - \pi_l(n) - E[c_{n2}] \tag{5}$$

is the revenue the seller can expect if the auction is run in the second period. The factor that varies across the different models is the value of α (for instance, $\alpha = p - q$ in the baseline model). Since we will show that α is independent of n, the effect of the number of buyers on the timing of sale is the same as that described in §4.2.

The important feature that all these models have in common is that there are two periods, and in the second period, all uncertainty is resolved. The condition

[8] Even if he has the highest possible draw for the cost, an entrant still obtains a higher value from buying the project than any incumbent.

then reflects the trade-off faced by the innovator: pay the extra development cost in the hope of extracting a higher revenue, proportional to the second-period revenue, or sell the project immediately.

5.1.1. Asymmetric Information About Value. We first consider the case where the innovator is better informed about the value of the innovation. We assume that the seller is perfectly informed of the value, whereas in period 1, the potential buyers believe that it is good with probability q and bad with probability $1-q$. The quality of the innovation is revealed at the beginning of period 2. The payoffs are otherwise the same as in the main model, and the innovator sells the good by running a second-price auction.

This asymmetric information can be because the innovator has greater familiarity with her own project and its performance in laboratory experiments than would a potential buyer. Indeed, asymmetric information is well understood to be a characteristic of markets for technology (Arrow 1971, Arora et al. 2001, Anton and Yao 2002), and a number of empirical papers have focused on how to address it. For example, Hegde (2014) examines how contracts are structured (e.g., milestone payments and royalties) in biomedical licensing when "tacit" knowledge or asymmetric information is important. Wuyts and Dutta (2008) show that social networks may reduce the problem of information asymmetries, and Danzon et al. (2005) stress the importance of experience as demonstrable evidence of an innovator's quality.[9]

In such an environment, if in equilibrium the seller with a good-type innovation sells in the first period, she can only extract profits $q(\pi(n)-\pi_l(n)-E[c_{n2}])$, since the buyer is unsure of the quality of the drug. A seller who knows that she has a good compound has an incentive to wait until the second period for the quality to be revealed. However, waiting is costly since the higher development cost Δ needs to be paid. The condition in the following proposition reflects this trade-off.

Proposition 5. *An innovator with a good project runs an auction, and thus sells the project, in the first period if and only if*

$$\Delta \geq (1-q)\big(\pi(n)-\pi_l(n)-E[c_{n2}]\big).$$

[9] Cockburn (2007a) reports in his analysis of survey data from the Licensing Foundation that "[t]hese results suggest severe problems with inadequate data and asymmetric information . . . . The critical role of ex ante imperfect or asymmetric information is also indicated by the high rates at which respondents cite revelation of new information about the end-user market or the performance of the technology as reasons to revisit contract terms" (pp. 10–11). We focus on asymmetric information rather than imperfect information, but we acknowledge that the latter is also likely to be important.

In Allain et al. (2013), we examine the robustness of these results. First, we show that our results hold if we relax the assumption that the low-type innovation has zero value. In this case, the low type always runs an auction in period 1, and there is a separating equilibrium where the high-type innovator runs an auction in period 2 if and only if the development cost is low enough. Second, we obtain qualitatively equivalent results if we model the sale as a sequential bilateral negotiation over fixed price contracts rather than an auction.

5.1.2. Asymmetric Information About the Number of Buyers. The source of the asymmetric information between the seller and the buyers could be of a different nature. Arora and Gambardella (2010) suggest there is uncertainty about the transaction process, and the seller might be better informed about it than the buyers. For instance, the seller might directly observe the number of buyers interested in her project, whereas the buyers are uncertain about the number of competitors they face.[10]

To capture this idea, we consider the following model in which there is no uncertainty about the quality of the project (everyone knows it is good), but there is asymmetric information about the number of buyers. The seller knows the number of buyers, but each buyer believes that he is the only one with probability p, or that there are a total of $n \geq 2$ buyers with probability $1-p$. In period 2, this information is revealed.

This is a signaling game in which the decision of whether or not to run an auction in period 1 conveys the innovator's information about the number of buyers. In particular, if the seller knows there is a single buyer, she will always run an auction in the first period since she cannot extract any revenue in the second. The timing of licensing will be determined by whether there exists a separating equilibrium in which, if she observes that there are n buyers, the seller waits for period 2.

Proposition 6. *There exists an equilibrium such that an innovator who knows there are n buyers runs an auction, and thus sells the project, in the second period if*

$$\Delta \leq \pi(n)-\pi_l(n)-E[c_{n2}].$$

The seller knows that if there are n buyers, she can extract revenues $\pi(n)-\pi_l(n)-E[c_{n2}]$ in period 2, since the buyers bid their values. A separating equilibrium exists as long as this value is greater than the cost of development.

Arora and Gambardella (2010) mention another potentially important idea. They cite a senior executive of a leading pharmaceutical firm who mentioned

[10] We thank an anonymous referee for this suggestion.

the winner's curse as a potential hurdle to transactions in markets for technology. In a scenario such as this, the buyers all have private information about the value of the project and underbid to avoid the winner's curse. The seller might then want to delay the sale so that information can be revealed. This provides an alternative explanation for delay, although the role of n in the timing of sale is unclear.

5.1.3. Differences in Risk Profiles. We examine a final possibility that yields a similar effect of the number of buyers on timing. Suppose the key difference between buyers and sellers is their risk profiles. In particular, we assume that both the seller and the buyers share the same belief about the prospect of the project (it is good with probability q), but they differ in the way they discount payments obtained in the second period:[11] the discount factor of the seller is δ_s; the buyers share a common discount factor δ_b. In this case we obtain the following result.

Proposition 7. *An innovator with a good project runs an auction, and thus sells the project, in the first period if and only if*

$$\Delta \geq (\delta_s - \delta_b)\big(\pi(n) - \pi_l(n) - E[c_{n2}]\big).$$

Proposition 7 yields a similar condition as in our baseline case, except that the potential benefits do not come from a difference in beliefs about the quality of the project, but rather from a difference in risk profiles. However, a trade-off exists only if $\delta_s > \delta_b$, which is unlikely to be the case if the biotech is the seller and the big pharma firms are the buyers.

Thus far, we have made no mention of real options, now a widely adopted approach to internal R&D management. The decision to develop a project from one phase to the next can be treated as the purchase of an option. In this framework, the "sell side" is usually ignored, whereas it is an integral feature of our model. In our context, a license contract involving an up-front payment with development milestones could also be interpreted as the sale of an option on the technology.

In a study of technology licensing contracts involving University of California inventions, Ziedonis (2007) found that option contracts (rather than immediate licensing) were more likely to be used when uncertainty about the underlying technology was high. The most likely purchasers of option contracts in his study were firms better able to assess the technology. In addition, purchasers able to absorb the knowledge underlying the technology had reduced incentives to license it after buying the option. These results highlight the potential for asymmetric information (as completely uninformed firms are less likely to participate in the market for technology) and moral hazard.

Ziedonis (2007) notes that competition for a project might increase the cost of delay, i.e., decrease the value of an early-stage option. Our model has slightly more subtle predictions for the effect of competition, but it is not inconsistent with the overall real options approach.

5.2. Other Explanations for Delay

In this section, we explore an alternative plausible explanation for the delay and show that the predictions are in conflict with some of our results on the effects of competition. We cannot, of course, rule out all other possible explanations, but we believe we have captured most of the relevant features of the pharmaceutical industry.

Our main model assumes that information about the project's quality increases over time. A plausible alternative assumption is information about the number of bidders. Specifically, the drug that is licensed is known to be good, but the number of bidders differs across periods. For instance, it is possible that the buyers engage in internal development in period 1 and enter the licensing market in period 2 if their internal efforts have failed. Alternatively, certain types of bidders, such as new entrants, might not have enough capabilities to assess the quality of the drug in the first period.

Regardless of why the number of bidders varies across periods, such a situation is likely to cause delays. Indeed, for an individual bidder, the expected gain from winning the license (net of costs) is independent of the period in which it is signed. What will change for the seller, however, is that the higher the number of bidders, the more draws taken from the cost distribution and thus the higher the winning bid.

We formalize these ideas in the following simple model. Assume that the total number of players is $n = n_1 + n_2$, where n_2 are the number of players who develop a drug internally and thus do not bid in the first period (by assumption) and n_1 is the number of bidders who do not develop and bid in both periods. Among those who develop the drug internally, some will be successful, others not. We call n_2^r the number of realized successes among the n_2 firms who try.

Suppose an auction is run in the second period after the realization of n_2^r. Then bidder i will bid her value:

$$\Pi(n_2^r + 1) - \Pi_l(n_2^r + 1) - c_i.$$

In period 1, the seller thus expects profits

$$E_{n_2^r}\big[\Pi(n_2^r + 1) - \Pi_l(n_2^r + 1)\big] - E_{n_1+n_2-n_2^r}[c_{n2}],$$

where $E_{n_2^r}$ is the expectation integrating over the distribution of the random variable n_2^r, and $E_{n_1+n_2-n_2^r}[c_{n2}]$

[11] We have ignored discounting thus far.

is the expected value of the second-lowest cost of the $n_1 + n_2 - n_2^r$ bidders, integrating over the distribution of the random variable n_2^r.

In the first period, a bidder i will bid

$$E_{n_2^r}\left[\Pi(n_2^r+1) - \Pi_l(n_2^r+1)\right] - c_i.$$

This is because the n_1 bidders cannot develop internally and that the n_2 nonbidders never bid in period 1. The seller thus expects the following profits from running an auction in period 1:

$$E_{n_2^r}\left[\Pi(n_2^r+1) - \Pi_l(n_2^r+1)\right] - E_{n_1}[c_{n2}].$$

Thus, the difference in expected profit from running the auction in period 2 rather than period 1 is only due to the number of bidders:

$$E_{n_1}[c_{n2}] - E_{n_1+n_2-n_2^r}[c_{n2}] > 0.$$

Indeed, in period 2 there are more bidders, so that the expected draw of the second-lowest cost is smaller. Overall, we have the following result.

Proposition 8. *The unique subgame perfect equilibrium is such that the project is sold in the first period if and only if*

$$\Delta \geq E_{n_1}[c_{n2}] - E_{n_1+n_2-n_2^r}[c_{n2}]. \tag{6}$$

The efficiency threshold increases in n_2.

The result of Proposition 8 differs from our baseline model with incumbents and entrants, if entrants are among the n_1 players who do not have the capacity to do internal development and the n_2 players correspond to the incumbents. Firms that market a product in the same narrow disease area seem more likely to engage in internal drug development, whereas those that are active in related diseases are less so. The empirical results presented above are more consistent with our main model than with this variant: we have shown in §2.4 that, in our data, delays become actually less likely if the number of incumbents increases.

Table 5 provides a summary of the five models described above.

6. Conclusion

We demonstrate that there is a robust empirical relationship between competition and the timing of licensing in the pharmaceutical industry. This is a setting where the market for technology is significant and where licensing has been occurring at later development stages. We find that an increase in the number of potential buyers has a nonmonotonic effect on the likelihood that a license is signed in a later stage of development. Further, we find that the type of potential buyer matters: an increase in the number of entrants is associated with later licensing, whereas we see the opposite pattern for incumbents. These results suggest that the effect of competition on licensing delays is economically significant.

We then develop a class of models that yields predictions consistent with these empirical patterns. As a baseline case, we present an auction model that incorporates a number of elements typical of markets for drug development projects in practice. Although normally we expect competition to increase efficiency, one of the important conclusions from our work is that competition has two countervailing effects on the efficiency of markets for projects. A decrease in the number of incumbents or an increase in the number of entrants on the market may inefficiently delay the sale of a project.

The theoretical finding that competition has countervailing effects on delays in licensing appears to be

Table 5 Summary of Model Characteristics

	Model				
Characteristic	Baseline	Uncertainty on value	Uncertainty on bidders	Risk profile	Internal development
Assumptions					
Players	$n > 1$ buyers	$n > 1$ buyers	1 or n buyers	$n > 1$ buyers	n buyers of different types
Discounting	$\delta_s = \delta_b$	$\delta_s = \delta_b$	$\delta_s = \delta_b$	$\delta_s > \delta_b$	$\delta_s = \delta_b$
Information	Seller overconfidence	Seller knows q	Seller knows n	Symmetric	Success rate of internal projects
Mechanism	Seller wants to wait as she is more confident that product is good	Seller wants to wait if she knows that product is good	In some equilibria, seller wants to wait if she knows there are n buyers	Seller less impatient than buyer	Buyers can develop compounds internally and buy from seller in period 2 if they fail
Predictions					
Fact 1	Yes	Yes	Yes	Yes	Yes
Fact 2	Yes	Yes	Yes	Yes	No
Fact 3	Yes	Yes	Yes	Yes	No

robust, so long as certain assumptions are met. Of particular importance is that uncertainty about the value of the innovation declines over time. We also explore several alternative assumptions about the nature of information, and we show that many yield predictions that are inconsistent with our empirical findings.

Though the pharmaceutical industry is particularly well suited for our application, our results should be relevant in any industry where the division of labor in the innovative process exists, where early-stage innovators have different beliefs or better information than later developers, and where innovators face a higher cost of providing information about quality through the development process than do potential buyers. One example of such an environment is university technology transfer. Projects generated by faculty may be difficult to transfer because academic scientists face a very high cost of proving their quality. They may lack the necessary equipment or staff to produce verifiable information, in addition to having an orientation toward basic research.

We do explicitly consider the role of intellectual property rights in this paper. Implicitly, we assume that patents provide clear property rights around an idea, which facilitates contracting. However, the strength or breadth of patents may also affect downstream competition and the timing of licensing. Weak patents, i.e., those that can be easily invented around or invalidated, are likely to be associated with a smaller payoff π. Broad patents that potentially exclude similar (not just identical) products may be more likely to generate "winner-take-all" outcomes downstream. As the strength and importance of patents varies across sectors, the role of intellectual property rights is an interesting extension to consider in future work.

Our model is not specifically designed to analyze the issue of mergers, but our results suggest that merger reviews in highly technological areas should consider this additional effect of the merger on upstream licensing markets. The pharmaceutical industry has undergone significant consolidation in recent decades, particularly between the large multinationals that are the typical buyers of licenses. In addition, there is much concern regarding a slowdown of innovation in this industry that the widespread use of licensing has failed to reverse. This paper highlights some frictions in licensing and the role of competition that may at least partially explain these patterns.

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Appendix A

Lemma 1

Second period. In the second period, the value of the innovation is known. If the innovation is good, an auction is run. The unique equilibrium is such that all buyers bid exactly their valuation (equilibrium bidding strategy in a second-price auction). Thus in the second period, bidder i bids $\pi(n) - \pi_l(n) - c_i$.

The profit of the seller is

$$p_2(n) = \pi(n) - \pi_l(n) - c_{n2}, \tag{A1}$$

and the profit of the buyer (with cost c) from winning the auction is

$$c_{n2} - c + \pi_l(n), \tag{A2}$$

where c_{n2} is the second-lowest cost among n draws of the cost parameter.

Proposition 1

First period. We show that it is a dominant strategy for buyer i with cost c_i to bid $b_i = q(\pi(n) - \pi_l(n) - c_i)$.

Case 1. Bid b_i is the highest bid. In that case, bidding more does not affect the payoff. Bidding less can make the bidder lose and yield payoff $q\pi_l(n)$. Bidding b_i yields payoff $q(\pi(n) - c_i) - b_{n2}$ (where b_{n2} is the second-highest bid). Since $q(\pi(n) - c_i - \pi_l(n)) > b_i > b_{n2}$, this deviation decreases the bidder's payoff.

Case 2. Bid b_i is not the highest bid. Denote the highest bid as b_1 in that case. Bidding less than b_1 does not change the outcome. Bidding more yields payoff $q(\pi(n) - c_i) - b_1$. This is an optimal deviation if $b_1 < q(\pi(n) - c_i - \pi_l(n))$. By definition of $b_i = q(\pi(n) - c_i - \pi_l(n))$, since $b_i < b_1$, this cannot be an optimal deviation.

In the first period, the seller thus expects a payoff $p(\pi(n) - \pi_l(n) - E[c_{n2}]) - \Delta$ if she waits for the second period, whereas she expects $q(\pi(n) - \pi_l(n) - E[c_{n2}])$ if she runs an auction. The proposition follows immediately.

Proposition 2

The efficiency threshold is given by

$$\underline{\Delta}(n) = (p - q)\big(\pi - \pi_l - E[c_{n2}]\big). \tag{A3}$$

As $E[c_{n2}]$ is decreasing in n (the higher the number of draws, the lower the expected second-lowest cost), we have $\underline{\Delta}'(n) > 0$.

Proposition 3
The threshold $\underline{\Delta}(n)$ decreases in n if $\pi(n)-\pi_l(n)$ decreases more than $E[c_{n2}]$. We have

$$F_{2n}(X) \equiv P(c_{n2} \le X) = \sum_{k=2}^{n} C_n^k F(X)^k (1-F(X))^{n-k}.$$

Hence the general formula of the second-order statistics of the distribution of c on $[\underline{c}, \bar{c}]$ is as follows:

$$E[c_{n2}] = \bar{c} - \sum_{k=2}^{n} C_n^k \int_{\underline{c}}^{\bar{c}} F(X)^k (1-F(X))^{n-k}\, dX.$$

If we assume a uniform distribution of c on $[0, \bar{c}]$, then c_{n2} follows a Beta$(2, n-1)$ distribution; thus $E[c_{n2}] = 2\bar{c}/(n+1)$. Then $\underline{\Delta}(n)$ decreases in n iff $\pi'(n) - \pi_l'(n) < -2c/(n+1)^2$.

The following example illustrates this case in a standard model of Bertrand competition with product differentiation. Assume that n buyers initially sell n symmetrically differentiated goods with a constant marginal cost $c \in [0, 1]$. They compete in prices. Following Motta (2004), we derive a simple model of consumer preferences from Shubik and Levithan (1980): the consumer's utility is given by

$$U(q_1, \ldots, q_n) = \sum_{i=1}^{n} q_i - \frac{n}{2(1+\mu)}\left[\sum_{i=1}^{n} q_i^2 + \frac{\mu}{n}\left(\sum_{i=1}^{n} q_i\right)^2\right],$$

where q_i is the quantity of good i consumed and μ is the degree of product substitution between the goods ($\mu \in [0, +\infty]$). The demand for each good is thus

$$D_i = \frac{1}{n}\left(1 - p_i(1+\mu) + \frac{\mu}{n}\sum_{j=1}^{n} p_j\right).$$

The innovation allows the introduction of a new product. If no license is signed, the market is composed of n symmetric firms with differentiated products. If one firm, say, n, signs a license with the (good) innovator, it introduces a new product. The competition game is now asymmetric, with the licensee selling two of the existing $(n+1)$ products. The equilibrium of the pricing game yields the following profits:

$$\pi(n) = \frac{(c-1)^2(1+n+\mu(n-1))(2+\mu+2n(1+\mu))^2}{2(1+n)^2(2-\mu^2+n(\bar{1}+\mu)(2+\mu))^2},$$

$$\pi_l(n) = \frac{(c-1)^2(1+n+\mu n)^3}{(1+n)^2(2-\mu^2+n(\bar{1}+\mu)(2+\mu))^2},$$

$$\text{for } i \in \{1, \ldots, n-1\}.$$

Whenever $\bar{c}$ is such that developing the innovation is profitable for the buyer with the highest cost (that is, $\pi - \pi_l - \bar{c} > 0$), tedious but simple computation shows that the efficiency threshold $\underline{\Delta}$ decreases in n for all $\mu > 0$, $n > 2$, and $c \in [0, 1]$.[12]

Proposition 4: Entrants and Incumbents
If the innovation is good, an entrant receives a profit $\pi_e(n+1)$ if he buys the license, whereas he receives a zero profit if he fails to buy it (irrespective of who buys it, he simply stays out of the market if he does not buy the license). An incumbent is assumed to receive $\pi(n)$ if he buys the license, $\pi_l(n+1)$ if an entrant buys the license, and $\pi_l(n)$ if another incumbent buys the license.

[12] Computations are available upon request.

We consider in turn the four possible cases:

Case 1. If $(\pi(n) - \pi_l(n) - c_{n1} \ge)\pi(n) - \pi_l(n) - c_{n2} \ge \pi_e(n+1) - c_{e1}$, then the two highest bidders (in each period) are incumbents. In the second period, if the innovator runs an auction, each entrant j bids $\pi_e(n+1) - c_j$, whereas each incumbent bids $\pi(n) - \pi_l(n) - c_i$. Consider the first period. If the innovator does not set up an auction, her expected gain is $p(\pi(n) - \pi_l(n) - c_{n2}) - \Delta$. If she sets up an auction in the first period, each entrant j bids $q[\pi_e(n+1) - c_j]$, whereas each incumbent bids $q[\pi(n) - \pi_l(n) - c_i]$, and an incumbent wins the auction. The expected gain for the seller is then $q(\pi(n) - \pi_l(n) - c_{n2})$.

The condition for the innovator to run an auction in period 1 is then

$$\Delta \ge (p-q)\big(\pi(n) - \pi_l(n) - E[c_{n2}]\big),$$

which is independent of e.

Case 2. If $\pi(n) - \pi_l(n) - c_{n1} \ge \pi_e(n+1) - c_{e1} \ge \pi(n) - \pi_l(n) - c_{n2}$, then in each period, the highest bidder is an incumbent and the second-highest bidder is an entrant; the condition for the innovator to run an auction in period 1 is then

$$\Delta \ge (p-q)\big(\pi_e(n+1) - E[c_{e1}]\big),$$

which increases in e.

Case 3. If $\pi_e(n+1) - c_{e1} \ge \pi(n) - \pi_l(n) - c_{n1} \ge \pi_e(n+1) - c_{e2}$, then either

- $\pi_e(n+1) - c_{e1} \le \pi(n) - \pi_l(n+1) - c_{n1}$, and, in any auction, an incumbent wins and pays the second-highest bid $\pi_e(n+1) - c_{e1}$. The condition for the innovator to run an auction in period 1 is then

$$\Delta \ge (p-q)\big(\pi_e(n+1) - E[c_{e1}]\big),$$

which increases in e; or

- $\pi_e(n+1) - c_{e1} \ge \pi(n) - \pi_l(n+1) - c_{n1}$, and, in any auction, an entrant wins and pays the second-highest bid $\pi(n) - \pi_l(n+1) - c_{n1}$. The condition for the innovator to run an auction in period 1 is then

$$\Delta \ge (p-q)\big(\pi(n) - \pi_l(n+1) - c_{n1}\big),$$

which is independent of e.

Case 4. If, finally, $\pi_e(n+1) - c_{e1} \ge \pi_e(n+1) - c_{e2} \ge \pi(n) - \pi_l(n) - c_{n1}$, in each period an entrant wins the auction. Then either

- $\pi_e(n+1) - c_{e2} \le \pi(n) - \pi_l(n+1) - c_{n1}$, and the second-highest bidder is an incumbent. The condition for the innovator to run an auction in period 1 is then

$$\Delta \ge (p-q)\big(\pi(n) - \pi_l(n+1) - c_{n1}\big),$$

which is independent of e; or

- $\pi_e(n+1) - c_{e2} \ge \pi(n) - \pi_l(n+1) - c_{n1}$, and, in any auction, the second-highest bidder is an entrant. The condition for the innovator to run an auction in period 1 is then

$$\Delta \ge (p-q)(\pi_e(n+1) - c_{e2}),$$

which increases in e.

The following condition guarantees that an entrant wins the auction and that the second-highest bid is always from an entrant:

$$\pi_e(n+1) - \bar{c} \geq \pi(n) - \pi_l(n+1);$$

under this condition, in both periods, the price paid to the innovator is $\pi_e(n+1) - c_{e2}$. The seller thus sets up an auction in the first period if and only if

$$\Delta \geq \underline{\Delta}_e(n) \equiv (p-q)(\pi_e(n+1) - E[c_{e2}]),$$

where $E[c_{e2}]$ is the expected value of the second-lowest cost among e draws of the cost parameter.

Note that $\underline{\Delta}_e(n)$ increases in e as $E[c_{e2}]$ decreases in e, whereas $\underline{\Delta}_e$ decreases in n as $\pi_e(n+1)$ decreases in n.

Proposition 5
In the second period, the type of the inventor is known, and the solution is the same as in Proposition 1.

First period. We show that the unique equilibrium is such that a player with cost c bids his expected valuation $q[\pi - \pi_l - c]$.

We first note that, for a buyer with cost c, bids strictly above $q[\pi - \pi_l - c]$ are dominated by bids equal to zero. We eliminate such strategies. After elimination of these strategies, we show that bidding exactly $q[\pi - \pi_l - c]$ is a dominant strategy for a player with cost c. Consider a bid $b < q[\pi - \pi_l - c]$. There are three cases to be considered:

Case 1. Bid b is the highest bid. In that case, bidding $q[\pi - \pi_l - c]$ does not change the outcome (outcome is purely determined by the second-highest bid).

Case 2. Bid b is not the highest bid. We denote by b_1 the highest bid in that case. If $b_1 > q[\pi - \pi_l - c]$, deviating to bidding $q[\pi - \pi_l - c]$ has no effect. If $b_1 \leq q[\pi - \pi_l - c]$, the expected profits if a bid $q[\pi - \pi_l - c]$ is made is $q[\pi - \pi_l - c] - b_1 \geq 0$. Thus bidding $q[\pi - \pi_l - c]$ is preferable to bidding b that gives zero profits.

In the first period, the innovator has to decide whether or not to run an auction. Her expected profit in an auction is $q[\pi - \pi_l - E[c_{n2}]]$. If she decides to wait for the second period to conduct the auction, she expects profits $\pi - \pi_l - E[c_{n2}] - \Delta$ if she is a good type and 0 otherwise. Thus a good innovator runs an auction in the first period if and only if

$$\Delta \geq (1-q)\big(\pi - \pi_l - E[c_{n2}]\big).$$

As Δ is known by all potential buyers, running an auction in the first period if this condition is not satisfied signals a bad-type innovator, and no buyer bids a positive price: such a deviation is therefore not profitable.

Proposition 6
In period 2, the buyers observe the actual number of buyers n. If an auction is run in period 2, and if $n \geq 2$, each of them thus bids $\pi(n) - \pi_l(n) - c_i$: the expected gain for the seller from running an auction in period 2 is $\pi(n) - \pi_l(n) - E[c_{n2}] - \Delta$. By contrast, if $n = 1$, the buyer bids 0 in period 2, and the expected gain for the seller of running an auction in period 2 is $-\Delta$.

We claim that if $\Delta \leq \pi(n) - \pi_l(n) - E[c_{n2}]$, there exists a separating equilibrium where

- the seller runs an auction in period 2 if $n \geq 2$;
- the seller runs an auction in period 1 if $n = 1$;
- if an auction is run in period 1, all buyers bid 0; and
- if an auction is run in period 2, each buyer bids $\pi(n) - \pi_l(n) - c_i$.

Assume that the seller follows the above strategy. Then if a buyer observes that an auction is run in period 1, he believes he is the only possible buyer and thus bids 0. All buyers do the same and the license is sold at a zero price; the seller gains 0. If, by contrast, no auction is run in period 1, in period 2 the real number of buyers is observed by all, and the seller gains $\pi(n) - \pi_l(n) - E[c_{n2}] - \Delta > 0$ if there are n buyers and 0 otherwise.

Consider a deviation by the seller, who runs an auction in period 1 although $n \geq 2$. Given the beliefs and strategy of the buyers, the deviation yields a zero profit instead of a positive profit: it is not profitable. Similarly, given the seller's strategy, no deviation by a buyer is profitable.

Proposition 7
In period 2, a buyer bids $\pi(n) - \pi_l(n) - c_i$ for a good idea and 0 for a bad one. Consider period 1. Waiting for period 2 to run an auction thus grants the seller an expected profit of $q[\delta_s(\pi - \pi_l - E[c_{n2}])] - \Delta$.

In period 1, by contrast, each buyer is ready to pay $q\delta_b(\pi - \pi_l - E[c_{n2}])$ for the license. Running an auction in period 1 thus grants the seller an expected profit $q\delta_b(\pi - \pi_l - E[c_{n2}])$.

So the seller runs an auction in period 1 if and only if

$$\Delta \geq (\delta_s - \delta_b)\big(\pi - \pi_l - E[c_{n2}]\big).$$

Discussion: Competition Among Licensors
Introducing several competing innovations is a very interesting extension of our paper. In what follows, we extend our base model to study this question and show that the effect of competition among licensors on the delay is ambiguous.

Consider the following model. Two innovators, each of them holding a preexisting project, can sell ("license") their ideas to n potential buyers. Ex ante, the two projects are similar in terms of potential payoffs: when developed in period 2, a good idea yields a profit $\pi^k(n)$, where $k \in \{1, 2\}$ is the number of projects developed. All buyers share the same common prior that each of the two projects is good with probability q, and the two innovators have the same prior that each project is good with probability p. We keep the assumption of overconfidence $p > q$. We denote by $\pi_l^k(n)$ the profit of a firm if k competitors develop a good project. Each buyer wants at most one license and can buy only one.[13]

The two periods are characterized as in the baseline model. In each period, a seller who has not yet sold her idea decides whether to run an auction. If only one project is for sale, a second-price auction is organized, whereas if the two ideas are for sale, a third-price auction takes place (a multiunit auction with a uniform price rule). In the latter case, each bidder can bid for only one project.

[13] We rule out strategic buying of a second license to prevent a competitor from developing an innovation.

Resolution. The equilibrium strategy for the buyers in period 2 is to bid their expected value for the good.

Lemma 2. *In the second period, if there are two good innovations for sale, or if there is only one innovation for sale and one good innovation has already been licensed in period* 1*, buyer* i *with cost* c_i *bids* $\pi^2(n) - \pi_l^2(n) - c_i$*. If there is only one good innovation for sale and no good innovation has been licensed in period* 1*, buyer* i *with cost* c_i *bids* $\pi^1(n) - \pi_l^1(n) - c_i$*.*

Proof. For the sake of presentation, we rename the potential buyers so that $c_1 \le c_2 \le c_3 \le \cdots \le c_n$.

Assume first that there are two good ideas for sale. Consider bidder 1 and assume that all other bidders bid their valuation. If he bids $\pi^2(n) - \pi_l^2(n) - c_1$, he gets one license at the price $\pi^2(n) - \pi_l^2(n) - c_3$, and bidder 2 gets the second license. His profit is thus $\pi_l^2(n) - c_1 + c_3$. Increasing his bid would not change his profit. Decreasing his bid up to $\pi^2(n) - \pi_l^2(n) - c_3$ would not change his profit, but decreasing it below $\pi^2(n) - \pi_l^2(n) - c_3$ would make him lose the auction and then receive $\pi_l^2(n) \le \pi_l^2(n) - c_1 + c_3$. Thus no deviation is profitable, and it is an optimal strategy for buyer 1 to bid his true valuation. The same applies for bidder 2. Consider now possible deviations by the $n-2$ other bidders, who lose the auction. To win the auction, buyer $i > 2$ would need to increase his bid up to $\pi^2(n) - \pi_l^2(n) - c_2 > \pi^2(n) - \pi_l^2(n) - c_i$: his profit would then be $\pi_l^2(n) + c_2 - c_i < \pi_l^2(n)$. Reducing or slightly increasing his bid does not change the profit of the bidder. Therefore, there is no profitable deviation for the $n-2$ potential buyers with the highest costs either: there exists an equilibrium where all buyers bid their true valuation.

Assume now that there is only one good idea on the market but that one license has already been sold in period 1 and the innovation is good. Then the same reasoning as above shows that all bidders bid their true valuation $\pi^2(n) - \pi_l^2(n) - c_i$. The winner is the bidder with the lowest cost among the ones who did not buy the license in period 1.

Finally, if there is only one good idea on the market, and if no license has been sold in period 1, or one license has been sold and the innovation is bad, everything is the same as in the main model, and all bidders bid their true valuation $\pi^1(n) - \pi_l^1(n) - c_i$.

Consider now the seller of a good project. If she runs an auction in the second period, her profit is $\pi^2(n) - \pi_l^2(n) - c_3$ if two good ideas are on the market, or one good license has already been sold in period 1, and $\pi^1(n) - \pi_l^1(n) - c_2$ if one good idea is on the market, and no good idea has been sold in the first period. Therefore, if she does not run an auction in period 1, she has an expected payoff of

$$p\big[p(\pi^2(n) - \pi_l^2(n) - E[c_3]) + (1-p)(\pi^1(n) - \pi_l^1(n) - E[c_2])\big] - \Delta.$$

We look for existence conditions of an equilibrium where both innovators participate in the auction in period 1. Note that we assume that, if a buyer buys an innovation in period 1 that turns out to be bad, he is informed immediately of the quality of the license.

Suppose the other innovator sells a license in the period 1 auction. Then

- if the innovator waits for period 2, she expects

$$p\big[p(\pi^2(n) - \pi_l^2(n) - E[c_3]) + (1-p)(\pi^1(n) - \pi_l^1(n) - E[c_2])\big] - \Delta; \tag{A4}$$

- if the innovator participates in the first-period auction, there are two licenses to sell. Bidders expect each of them to be good with probability q. As before, there is an equilibrium where each bidder bids his true valuation. Both licenses are sold to the two bidders with the lowest costs, and the expected profit of each seller is thus

$$q^2\big(\pi^2(n) - \pi_l^2(n) - E[c_3]\big) + q(1-q)\big(\pi^1(n) - \pi_l^1(n) - E[c_3]\big). \tag{A5}$$

Therefore, if her competitor runs an auction in period 1, an innovator participates in the auction if and only if (A5) is higher than (A4), which yields the following proposition.

Proposition 9. *There exists a subgame perfect equilibrium such that the two projects are sold in the first period if and only if*

$$\begin{aligned}\Delta \ge \underline{\Delta}_2 \equiv{}& (p^2 - q^2)\big(\pi^2(n) - \pi_l^2(n) - E[c_{n3}]\big) \\ &+ [p(1-p) - q(1-q)](\pi^1(n) - \pi_l^1(n)) \\ &- p(1-p)E[c_{n2}] + q(1-q)E[c_{n3}].\end{aligned}$$

Comparative Statics. Competition will reduce delay if $\underline{\Delta} - \underline{\Delta}_2 > 0$. We have

$$\begin{aligned}\underline{\Delta} - \underline{\Delta}_2 ={}& (p^2 - q^2)\big[(\pi^1(n) - \pi_l^1(n)) - (\pi^2(n) - \pi_l^2(n))\big] \\ &+ (p^2 - q)\big(E[c_{n3}] - E[c_{n2}]\big).\end{aligned}$$

Under the overconfidence assumption, $p^2 - q^2 > 0$; besides, $E[c_{n3}] - E[c_{n2}] > 0$. However, the sign of the other terms is ambiguous.

- The sign of $p^2 - q$ varies with the difference between the priors of the innovators and the priors of the potential buyers. If the priors are close, then $p^2 - q < 0$. The priors need to be very different for $p^2 - q$ to be positive.
- The sign of $(\pi^1(n) - \pi_l^1(n)) - (\pi^2(n) - \pi_l^2(n))$ is ambiguous too. For instance, in the Bertrand model with differentiated products developed above, we can show that competition reduces the value of the license when the products are not too close substitutes, that is, $(\pi^1(n) - \pi_l^1(n)) - (\pi^2(n) - \pi_l^2(n)) > 0$ (respectively, < 0), if μ is low (respectively, high).

Therefore, the overall effect of competition on delay in licensing is ambiguous. The entry of a second innovator may either increase or decrease delays in licensing.

Appendix B. Alternative Definitions of Potential Buyers

An important concern in the empirical analysis is that our key variables of interest, those for buyer competition, may be measured with error because we cannot observe for certain which firms may have considered a license for a particular drug candidate. In this section, we explore alternative definitions of potential buyers. Our previous definition was based on the argument that firms with market experience in related areas would have the highest valuation

for, and best ability to evaluate, potential drug candidates. In her paper on licensing of biotechnology drugs, Levine (2007) defines a potential buyer as any firm that markets a biotechnology product in the United States and allows their valuation to depend on their experience in different disease areas. We consider non-U.S. markets and do not distinguish prior marketing of a biotechnology product from that of small-molecule drugs, but our previous definition also restricted the set of potential buyers to those that actually buy a license at least once in our data. In this section, we consider two alternative definitions of potential buyers to check the robustness of our findings.

First, we define incumbents and entrants as before except without the restriction that firms buy a license at least once in our data set. This set includes many firms that may not be seeking to license in external drug candidates. For example, a small firm that codeveloped a drug with a much larger partner, but that has no marketing capabilities of its own, is counted as a potential buyer under this definition. Table B.1 presents the results from our three econometric models using this alternative definition. We again find a negative and significant coefficient on the number of incumbents and a positive and significant coefficient on the number of entrants. Second, we define incumbents and entrants as in the previous section except that we restrict buyers to be large, publicly traded firms (those we believe are most likely to have the necessary commercialization and marketing skills). The results, presented in Table B.2, are weaker in terms of statistical significance though of the expected signs. Because most big firms are active in a large set of disease areas, there is less variance in the number of potential buyers across therapeutic classes for us to identify the effect of competition. As before, both tables report only the coefficients relevant to market structure, but all specifications include the same control variables as the baseline case.

Table B.1 Results with First Alternative Definition of Potential Buyers

Variable	Logit	Ordered logit	Hazard rate
Incumbents	−0.0035**	−0.0058**	−0.0025*
	(0.0016)	(0.0013)	(0.0013)
Entrants	0.0058**	0.0045**	0.0068**
	(0.0017)	(0.0014)	(0.0015)
Number of obs.	1,633	1,633	1,449
Log L or R^2	−927.4660	−2,072.446	0.095

Note. L, likelihood.
* and ** denote significance at the 10% and 5% levels, respectively.

Table B.2 Results with Second Alternative Definition of Potential Buyers

Variable	Logit	Ordered logit	Hazard rate
Incumbents	−0.0254	−0.0496**	−0.0031
	(0.0211)	(0.0177)	(0.0175)
Entrants	0.0232*	0.0106	0.0337**
	(0.0127)	(0.0104)	(0.0105)
Number of obs.	1,633	1,633	1,449
log L or R^2	−932.5247	−2,081.531	0.087

Note. L, likelihood.
* and ** denote significance at the 10% and 5% levels, respectively.

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