# Licensing and Scale Economies in the Biotechnology Pharmaceutical Industry

Anna Levine*
Stanford University

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**Abstract**

This paper empirically quantifies the effect of licensing market competition on incentives for innovation in the biotechnology pharmaceutical industry. My estimates are based on the current distribution of domestic marketing rights and assumptions about how this distribution relates to firms' underlying profit functions. I find that pharmaceutical marketing firms' values for adding a new drug to their product portfolio depend on the distribution of the other products marketed in the same physician specialty as the drug, the size of the patient market the drug serves, and the number of physicians in the physician specialty that prescribes the drug. When the distribution of marketing rights for products in a physician specialty are concentrated in a single firm, the bargaining position of the innovator is weakened and this effect becomes more severe as the size of the physician specialty increases. The difference between the firm with the highest valuation and the firm with the second highest valuation increases by an average of 2% for every additional 10,000 physicians in a specialty.

## 1 Introduction

In many innovative industries the majority of innovation occurs in a large number of small firms while marketing and commercialization are done by a smaller number of large firms. This is particularly true in biotechnology where less than one third of biotechnology pharmaceuticals are marketed by the firms who brought them into phase one FDA trials. Most marketing rights in this industry are transferred from the innovating firm either through a license or acquisition to another firm that markets the product. The size distribution of innovators is shown in Figure 1 while the size distribution

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of marketers is show in Figure 2. In this paper I develop an econometric model to quantify the forces driving this consolidation of products across firms.

Consolidation of marketing impacts the level of competition in licensing markets and the return an innovator will receive from successful innovation. The structural model of licensors' profits I estimate allows me to quantify how the split of overall producer surplus an innovator receives varies with product characteristics. When marketers' values for adding a given product to their portfolio vary widely, particularly at the top of the value distribution, the return an innovator receives upon successful innovation is depressed. The problem is more severe when the innovator does not have the capabilities to market their product themselves. This lack of competition allows large marketing firms to extract value leaving a smaller proportion of overall producer surplus for innovators.

My estimates use data on the current distribution of domestic marketing rights and assumptions about how this distribution relates to firms' underlying profit functions. Specifically I assume the distribution of products across firms is a locally pairwise stable allocation. This means that no two firms could make higher profits if one firm sold the marketing rights of one of their products to another firm, or if the two firms traded single products with an accompanying transfer. Using the revealed preference inequalities implied by local pairwise stability, I proceed with estimation using a matching estimator developed recently by Fox (2007).

Throughout the paper, I refer to physician class/specialty and disease/indication class. Drugs in the same indication/disease class compete with one another to be prescribed by a physician when a patient has a particular disease or disorder. However, drugs in the same physician class/specialty (but not in the same indication class) do not compete with each other to be prescribed for a given patient. For example, if one drug treats Rheumatoid Arthritis and another drug treats Multiple Sclerosis, these drugs do not directly compete against each other to be prescribed for a particular patient (i.e. they are not in the same indication class), but they are in the same physician class - Rheumatology.

In my analysis I find that the economies of scale firms realize from marketing multiple drugs in the same physician specialty and the diseconomies of scale firms encounter when growing the overall size of their product portfolio are important factors in explaining differences in firms' valuations for licensing a particular product. An incumbent firm's return from deterring entry of new firms into a

product market or a physician class, is also important. Additionally, I find that innovators are more likely to keep products they innovate particularly when the innovator already has cash flow from another successful product.

Using my parameter estimates I calculate each potential marketing firm's value for adding a product to their portfolio. My estimates show that when the marketing rights of products in a physician specialty are concentrated in a single firm, the bargaining position of the innovator of a new drug in this physician class is weakened. This effect becomes more severe as the size of the physician specialty increases. An increase of 10,000 physicians in a specialty on average increases the difference between the firm with the highest valuation and the firm with the second highest valuation by an average of 2%.

My results have important implications for merger analysis. Preserving competition in the licensing market is important to ensure innovation incentives. Therefore, when considering the effect of a merger, policy makers should consider the effects on competition in the licensing market in addition to traditional considerations about the downstream market. This is a particularly important force to consider in physician specialities where the concentration of marketing rights across firms is high even when these products do not compete in the downstream market.

Historically, large traditional pharmaceutical firms were highly involved in the research and development of new pharmaceutical products. Today the bulk of research occurs in small venture capital backed firms. At the same time, the direction of drug development has shifted towards drugs treating niche diseases prescribed by specialists with few if any other treatments. Possible explanations for this shift include changes in the nature of research and an increase in capital available to support start-up firms. My paper suggests a third contributing factor: as research has shifted towards niche markets, startup innovators no longer face the threat of hold up in the licensing markets. In niche markets large marketing firms are not able to extract value from new innovators and therefore these innovators receive a larger proportion of total producer surplus.

Several related studies analyze licensing, mergers and acquisitions in the biotechnology pharmaceutical industry. In Danzon, Epstein, and Nicholson (2004), the authors look at the predictors of merger activity and the subsequent impact of mergers on firm growth. Consistent with my results,

they identify the importance of established distribution networks, and financial distress of small firms as important drivers for merger activity. My analysis also reveals how the importance of these forces may vary across different disease markets in this industry.

Gans, Hsu, and Stern (2002) examine a cross section of innovative industries and find that when complementary asset ownership is more important, innovators are more likely to either license or be acquired by larger incumbent firms. The authors use a survey in which firms report how important complementary assets are for commercializing their products. In this paper, I identify the characteristics of the markets within the industry for which these complementary assets are important and to what extent these market characteristics drive the licensing patterns we observe in this industry.

In section 2, I describe the industry. In section 3, I present a basic empirical model and describe the stability assumption I make on market outcomes which I use for my later estimation. In section 4, I describe the data used in my analysis. In section 5, I present descriptive empirical results. In section 6, I present my estimation strategy, and my empirical results. I conclude in section 7.

# 2 Industry Description : Biotechnology Pharmaceuticals

## 2.1 Industry Overview

Beginning in 1980 there have been hundreds of firms founded that specialize in the field of biotechnology pharmaceuticals. Biotechnology pharmaceuticals treat a wide range of diseases; some biotechnology drugs treat common ailments such as diabetes whereas other drugs treat extremely rare disease such as Gaucher disease. Over one half of biotechnology drugs treat orphan diseases. Orphan diseases affect less than 200,000 people in the United States. In addition, some biotechnology drugs treat ailments for which they are the only available treatments while others treat conditions with many treatment options.

Biotechnology pharmaceuticals differ from traditional small molecule drugs in their research processes and the types of markets they serve. Biotechnology innovation relies heavily on the tools of molecular biology. Biotechnology drugs are produced using living organisms, which makes process innovations an important part of biotechnology research. In addition, the biotechnology discovery process is more directed than small molecule research. For example, a particular protein may be

known to be missing for a particular patient population. Research focuses on finding ways to produce this protein. To a large extent, firms involved in small molecule research (traditional pharmaceutical firms) cannot use their research capabilities from that sector to help them develop biotechnology drugs. However, firms that have established relationships marketing traditional pharmaceuticals can leverage that experience to market biotechnology pharmaceuticals. Traditional pharmaceutical firms are involved more in the marketing of biotechnology drugs than in the innovation of these drugs as shown in Figure 3.

Direct to physician marketing is an important aspect of marketing products in the biotechnology pharmaceutical industry. In many cases, the diseases these drugs treat are life threatening and the importance of direct to consumer advertising is diminished. Direct to physician marketing includes making visits to doctors, creating events that doctors will attend and/or advertising in the publications doctors read. Creating contacts with physicians is both extremely important and costly. In addition, relationships with physicians can be leveraged across multiple drugs (NY Times May 2007). For example, pharmaceutical firms typically hire a sales force for a physician class, and a sales team member can market multiple drugs in a physician class.

Marketing rights are sold either for a lump sum, or more commonly for a lump sum plus a royalty. In addition, many innovating firms are acquired by larger firms. Table 1 describes the current operating status of 73 of the 100 innovators in my sample. Thirty-one of these firms are still operating autonomously. The other firms were either acquired, merged with another firm or filed for bankruptcy. Table 2 shows the product portfolio size for the firms that were acquired or merged at the time of acquisition or merger. Fourteen of these firms had control over no currently approved products at the time of merger or acquisition while 17 had control over only one product. From these figures we see that most firms acquire marketing rights not though an acquisition or merger but though the licensing market. These figures also show that even when firms acquire marketing rights through other means, they typically only acquire the rights of a single approved drug.

Licensing decisions are made for a variety of reasons. A marketing firm may be looking to fill a place in their portfolio, and therefore they may actively seek out licensing partners who can fill that need. Also an inventor often looks for partners for drugs they can not profitably market themselves.

For example, consider a small innovative firm that is developing a treatment for rare cancer and a drug for over active bladder (OAB) syndrome under development. The small firm knows that they must license the OAB drug because it serves a large market and it is prescribed by primary care physicians. The small firm will not be able to develop a large enough sales force to bring this drug to market. Therefore it will actively look for partners. However, the firm might consider bringing the Oncology drug to market on its own. The impact of the variation in the size of the physician specialty that prescribes a drug as well as variation in the overall size of the patient population with the disease a drug treats on the return different firms receive from bringing a product to market will be quantified in my estimation.

There may be benefits an innovator receives from keeping the marketing rights of the products they have innovated. In particular, innovators may have developed relationships with physicians during the development process that they can later leverage when commercializing the drug. In addition, they may have private information about the true quality of the drug or the potential for future drug development within a disease class. Many firms in my sample were venture capital backed when they were founded. Most of these firms had an initial public offering before their first successful drug was approved. Anecdotal evidence suggests that cash flow pressures often force young firms into licensing agreements. Consistent with these stories, we will later see empirically that new innovators are more likely to license their first approved product than subsequent products.

# 3 Empirical Model

In this section I discuss the empirical model I use in my estimation. First I introduce some basic notation, assumptions and describe the value function I use for my estimation. Then I present the solution concept. In the last part of this section I discuss how my empirical estimates relate to innovation incentives.

Let $I$ be the set of all products and $J$ be the set of potential marketers for these products. I will abuse notation by letting $I$ and $J$ also be the number of products and potential marketers respectively. Let $B_j$ be the set of products marketed by firm $j$. An allocation $B = (B_1...B_J)$ is a partition of the products. Let $V_j(B)$ be firm $j$'s valuation from marketing the bundle $B_j$ given the total industry

allocation $B$. I allow firm $j$'s value to depend on the portfolios of other firms, for instance because a firm may care about whether rival products are marketed just by one firm or by several firms.

I take the location of innovation as exogenous. I assume firms care about maximizing profits, and innovator's profits are additively separable across each of their innovations.

## 3.1 Firm Value Function

I am interested in understanding the market structure of drug marketing and distribution, so the model focuses on capturing the differences in product values across prospective marketing firms. Roughly there are three potential reasons a firm might have a high value for marketing a given drug. First, an innovating firm may have a reason to value its own drug more than any other firm. Secondly, a firm already marketing another drug in the same disease market may have an incentive to deter entry of new firms into that market. Finally, firms may realize scale economies in the overall size of their product portfolio or when marketing multiple drugs that are prescribed by physicians in the same specialty.

Innovators may value marketing a drug more than other potential marketers due to the special knowledge they have about the drug and the relationships with physicians they have formed during drug development. At the same time, new innovators may face cash constraints that prohibit them from hiring the sales force necessary to successfully market a drug. I therefore allow a potential marketer $j$'s value to depend on whether they were the innovator of the drug, $I_{ij}$, and allow the impact of this advantage to depend on the availability of cash flow from previously approved products, $H_j$.

The level of competition a product will face may affect a potential marketing firm's value from marketing a drug. I will allow for two types of competitive effects in firms' value functions: competition at the disease class level (product market) and competition at the physician specialty level (licensing market). The level of competition in a disease class may impact a firm's profit from having the marketing rights to particular drug. There may also be competitive effects in the licensing market. In particular, as there are more competitive bidders for products in a physician specialty the proportion of producer surplus that goes to the innovator increases. Therefore, marketers may have an incentive to deter entry of other firms into a physician specialty. Allowing for competitive externalites implies

that firm $j's$ value for marketing products $B_j$ depends on the industry-wide allocation of products $B$. The level of competition that product $i$ faces given industry allocation $B$ is $Comp_i(B)$.

I let $M(B_j)$ be firm $j$'s cost for marketing bundle $B_j$. I will allow $M(B_j)$ to have scale economies at the physician specialty level as firms may be able to realize economies of scale when marketing multiple drugs in the same physician class. In addition, I allow for decreasing returns to scale at the total product portfolio level. Anecdotal evidence suggests that a major cost for adding a product to a firm's current portfolio is the cost of their attention; coordinating the marketing of a new product distracts the firm from the other products they are also marketing. I allow for these costs $P$ to rise with the size of the product portfolio, $|B_j|$.

$$V_j(B) = \sum_{i \in B_j} ( \underbrace{\alpha_i}_{Inherent\ Value} + \underbrace{I_{ij}(H_{ij})}_{Innov.\ Adv.} + \underbrace{Comp_i(B)}_{Level\ of\ Competition} ) \underbrace{-M(B_j) - P(|B_j|)}_{Marketing\ channels\ in\ place} \underbrace{+ \sum_{i \in B_j} \epsilon_{ij}}_{Idiosyncratic\ value} \quad (1)$$

I let $\alpha_i$ be the inherent profitability of marketing product $i$ ; $\alpha_i$ is the value a firm has for marketing product $i$ that does not vary across firms.

## 3.2 Identifying Assumptions on Market Outcomes

I draw on the matching literature and the literature on coalitional (cooperative) games to define a solution concept that assigns to any set of firm profit functions a set of potential licensing market outcomes. Specifically, I assume the market allocation is locally pairwise stable. An allocation $B$ is locally pairwise stable if there do not exist two firms that could make higher profits if one firm sold the marketing rights of one of their products to the other firm, or if the two firms traded single products with an accompanying transfer. Formally for any allocation $B$, consider the set of allocations derived from trades between firm $j$ and $j$' defined by $\Theta^B_{j,j'}$:

$$\begin{aligned} \Theta^B_{j,j'} = \{(B_1, ..\widetilde{B_j}...\widetilde{B_{j'}}...B_J) | (\widetilde{B_j}, \widetilde{B_{j'}}) \in \ & \{(B_j - \{a\} \cup \{b\}, B_{j'} - \{b\} \cup \{a\}), a \in B_j, b \in B_{j'}\} \\ & \bigcup \{(B_j - \{a\}, B_{j'} \cup \{a\}), a \in B_j\} \\ & \bigcup \{B_j \cup \{b\}, B_{j'} - \{b\}, b \in B_{j'}\} \ \} \end{aligned} \quad (2)$$

$\Theta^B_{j,j'}$ includes the subset of all partitions of size $J$ of the set of products $I$ where firm $j$ and firm $j$' switch single products from the allocation $B$ or firm $j$ increases (decreases) the size of its portfolio $B_j$

by one product and firm j' decreases (increases) the size of its portfolio $B_{j'}$ by one product. Looking across all pairs of firms, I define $\Theta^B = \bigcup_{j=1}^{J} \bigcup_{j=j+1}^{J} \Theta_{j,j'}^B$. An allocation $B$ is locally pairwise stable if:

$$\forall B' \in \Theta^B \ , \quad V_j(B) + V_{j'}(B) > V_j(B') + V_{j'}(B') \tag{3}$$

For a given set of profit functions there may be more than one locally pairwise stable allocation.

Note that in the model I have defined, local pairwise stability is a weaker solution concept than the core or competitive equilibrium. Any allocation in the core must be locally pairwise stable, but must also be jointly profit maximizing for all the firms in the market. I am loathe to impose such a strong assumption in a market that is imperfectly competitive. Under local pairwise stability groups of more than two firms cannot coordinate on a deviation, so instead if the value to a firm from an action is greater than the externality imposed on any single firm but less than the sum of the externalities imposed on other firms the resulting outcome would still be locally pairwise stable even though it is not in the core.

In this industry there may be nonlinear costs to increasing the size of a firm's product portfolio rapidly or coordinating actions across many firms as well as regulatory constraints which prevent multi-product or multi-firm trades or acquisitions from occurring. I therefore do not want to assume these types of trades exist.[1]

In the presence of complementarities the value of a firm for a product A and a product B separately may be less than the value of the firm for product A and B together. Hence considering single product bilateral deviations is not sufficient to show there are no multi-product acquisitions involving many firms which would make all firms better off. For example, suppose firms have concave marketing cost functions and consider the allocation of products $\{A, B, C\}$ all in different product markets but in the same physician class across firms 1, 2, and 3. Suppose firm 1 innovated product A, firm 2 innovated product B, and firm 3 innovated product C. Suppose the extra value an innovator receives for marketing their own innovation is 3. The value of a firm of marketing any single product (excluding the value an innovator receives for marketing their own innovation) is 1, any two products is 4 and all three products is 15. In this case, the aforementioned allocation, one product in each of the three

[1]In Roth et al. 2004 in designing the mechanism for kidney exchange they find greater than two way exchanges face large coordination costs hence only consider pairwise trades.

firms, would not be in the core, but it would be locally pairwise stable.

Using the local pairwise stability assumption on the current allocation I will be able to identify the drivers of the differences in firms' profits. Forces which affect the valuation of all firms equally, for example the inherent profitability of a drug, will difference out of the pairwise stability inequalities and hence will not be identified. I will defer the discussion of the specific parametrization of the value function, as well as the specific assumption I will make on the distribution of $\epsilon_{ij}$ until later.

## 3.3 Relationship to the Incentives for Innovation

In this section, I make a specific assumption about how a single new drug might be allocated and show how the innovator's value changes with the distribution of potential licensing partners' values to license this product. This section relates the drivers of the differences in firms' profits to the incentives for innovation, and in addition will be used as a framework for my later counterfactuals.

Consider the decision of an innovator to develop a new drug taking the allocation of all currently approved drugs as fixed. The decision to innovate depends on the total return from innovating that drug and hence on the marketing value the innovator and all potential licensors will have for the innovated product.

I assume there is some firm independent value $\alpha_i$ from marketing product $i$ and some value $D(X_{ij})$ which depends on $X_{ij}$ which are characteristics of the marketing firm and the product.

Therefore, the marketing valuation of firm $j$ for product $i$ is:

$$V_{ij}^M = \alpha_i + D(X_{ij}) \tag{4}$$

Suppose that firm $k$ gets the opportunity to innovate drug $i$ at some cost $C_k^i$, and the lowest cost innovator, the innovator with the lowest $C^i$, gets the opportunity to invent first. Therefore, the first innovator who has positive value from innovating a product innovates and no other firm can innovate the same product.

After a product is innovated the marketing rights of the drug are sold to the firm with the highest valuation of the drug, or kept by the innovating firm if the innovator has the highest value. Next I will show that when the values of potential licensors of a product vary widely at the top of the

value distribution an innovator with a low value for marketing the product herself gets held up in the licensing market.

Rank potential licensors in terms of marketing values $V_{iJ}^M$, $V_{iJ-1}^M$ etc where firm $J$ has the highest valuation from marketing product $i$. If the innovator, firm $k$, has the highest valuation that is $V_{ik}^M > V_J^M$ then the innovator will not license the drug and value from innovation to firm $k$ is equal to:

$$V_{ik}^I = V_{ik}^M - C_k^i \tag{5}$$

Otherwise the return from innovation for firm $k$ is as follows where $\gamma$ is the bargaining coefficient:

$$V_{ik}^I = (max(V_{ik}^M, V_{iJ-1}^M) + \gamma * (V_{iJ}^M - (max(V_{ik}^M, V_{iJ-1}^M)) - C_k^i \tag{6}$$

Therefore we see that the returns to innovate increase in both the levels of the $V_i^M$'s and in the concentration of the $V_i^M$'s. The later point is due to the holdup problem.

When the spread of $D(X_{ij})$ is large and the difference between $V_J^M$ and $V_{J-1}^M$ is large innovation may be skewed. In this case the most efficient innovator, the innovator with the lowest $C_j^i$, may not find it profitable to innovate as there is a large potential for holdup in the downstream market. Therefore, in this case the return from innovation depends on the innovator's ability to market the products themselves and innovation will be skewed towards "good" marketing firms. Also in this case some products which would be innovated in the presence of a competitive licensing market may not be innovated. For the purpose of my empirical analysis I will assume this is not the case.

In my paper I seek to quantify the determinants of the magnitude and variance of $D(X_{ij})$ across firms for different downstream product markets. These are of interest as they reveal information about the competitiveness in the licensing market, and identify in which markets the distortion of the returns on innovation across firms will be most severe.

The mean of $V_{ij}^M$'s will also affect the incentives of innovating firms to innovate. I cannot however identify the mean of the $V_{ij}^M$'s as I do not have data on the sales and revenue received by firms when marketing a particular drug. If I had this information I would be able to identify $\alpha_i$ and hence the mean value of the $V_{ij}^M$'s. As the mean shifts upward the return to an innovator will increase and if we take the variance as fixed (as well as the outside options and innovation costs) the probability that

innovation is skewed will decrease. However if the costs of innovation shift 1-1 with the upward shift in the mean value of the $V_{ij}^M$'s the return to innovation will remain the same.

# 4 Data

## 4.1 Data Construction

My sample includes 149 tradenames of biotech drugs approved between October 1982 and July 2006. Figure 4 shows the FDA approval dates for the drugs. A tradename is included in my sample if in July 2006 it was listed as an approved biotechnology drug on both the Recombinant Capital Database and on the Biotechnology Industry Organization websites.

Information about the innovators of each drug, as well as information about product licensing comes from the Recombinant Capital Database, a proprietary database documenting the clinical development activities and marketing alliances of biotechnology firms. I have added to and cross referenced this information using press releases from companies, as well as company 10-K reports. The current marketer of each drug was collected from company websites and verified using company 10-K reports.

In my analysis I only use information about which firm had control of domestic marketing rights when the drug went into phase 1 trials (innovator) and who is currently marketing the drug in the US (marketer). From the Recombinant Capital Database I have information on 385 licensing agreements, 144 involving the domestic marketing rights of these 149 biotech tradenames.[2]

For each marketer of a biotech drug, excluding large traditional pharmaceutical firms (for example Merck), I gathered information about their entire product portfolios. For each innovator of a drug the approval dates for all of the products they have innovated were ordered and this ranking is used as a proxy for the presence of cash constraints.

[2]I have definitive information on which firm had marketing rights when the product entered phase one trials and who is currently marketing the drug. I used 10-K reports and press releases to verify this information when it was available in the Recombinant Capital Database and when it was not available this information comes directly from these alternative sources.I do not have comprehensive information on licensing deals occurring between phase one and today; if firm A licensed to firm B in phase 2 who in turn licensed to the current marketer C after the product was approved by the FDA then in my estimation I will say firm A is the innovator and firm C is the marketer. I do not use information that firm B had marketing rights from phase 2 until approval. I do not have comprehensive information about these "intermediate" licensing arrangements and therefore I interpret 144, the number of licensing deal I have information on, to be a lower bound on the total number of times the domestic marketing rights of these 149 tradenames have been transferred from one firm to another.

The approved indications for a drug as well as approval dates for these drugs were obtained from the FDA website. The drugs were then classified into physician specialties, that is which types of physicians prescribe the drug, and then within a physician specialty I classified the drugs into indication classes, that is which drugs treat the same conditions. This classification as well as information about the market size of the indication and controls for the other available treatments for a disease not already included in my dataset has come from numerous interviews with physicians.

In my physician interviews I had physicians rank the diseases (treated by drugs in my sample) that are cared for by physicians in their physician specialty from 1-5 in terms of the frequency a typical physician in their physician class treats the disease; 1 is rare and 5 is common. The relative markets size of a indication class within a physician class is used as a proxy for the relative level of the marketing cost required to market a drug in given physician class.[3]

Information on alternative treatments available as well as which drugs compete with each other was cross referenced using the databases Micromedex, Uptodate, and as well as several medical textbooks. I use the number of other treatments for a disease obtained through physician interviews, as well as the number of firms marketing these treatments as proxies for the level of competition a product faces in a given disease market. Similarly, the number of other products in a physician class, as well as the number of firms marketing these products are used as a proxies for the level of competition in a given licensing market.

The number of physicians in a physician class was collected from the AMA (American Medical Association) website. The size of physician specialities represented in my sample varies from 2,452 physicians classified as Vascular Surgeons to 99,913 physicians classified as General Practitioners. Figure 6 shows the number of physicians in each of the twenty-five physician classes in my sample. The number of physicians in a physician specialty is used a proxy for the relative level of the marketing costs required to market a drug in that specialty.

## 4.2 Basic Summary Statistics

Many of the drugs in my sample treat multiple diseases. These 149 biotech drugs were classified into 182 indication classes treating different diseases/disorders. A product is defined as a firm, tradename,

[3]Market size information from these interviews was cross referenced with Medicaid prescription drug information.

indication class combination. There are a total of 294 biotech products in my sample. Between one and four firms in my sample have products in a given market/indication class. On average there are 1.5 biotech drugs in each indication class and on average a total of 3 treatments for each indication.[4] Figure 5, presents a histogram of the number of biotech pharmaceuticals in a given indication class.

There are twenty-five physician classes that span the 182 indication classes treated by one of the biotech drugs in my sample. On average there are seven indication classes in each physician class, and there are on average 12 products in each physician class. Oncology, the physician class with the largest number of products, has 51 products. Figure 6 shows the allocation of biotech pharmaceuticals across physician classes.

# 5 Descriptive Analysis

In this section I use basic logistic regressions to consider two related questions. The first estimation examines what variation in innovator characteristics and product market characteristics are associated with innovators marketing the products they innovate. In the second set of regressions the estimation is expanded to study how the interaction of firm and product characteristics predict which of the potential marketers end up with commercialization rights. Throughout this section the allocation of a single product is considered taking the allocation of all other products as fixed.

The results presented in this section are designed to be descriptive in nature; these preliminary results motivate the parametrization of the model used in my later estimation. Under assumptions discussed later, the estimates are also consistent estimators of the drivers of the differences in firms profits. The results in this section are qualitatively and quantitatively very similar to the results of my later estimation.

## 5.1 When do innovators keep the marketing rights of the products they innovate?

Less than one third of the products in the sample are marketed by the firms who innovated them. On average innovating firms have successfully innovated three to four products. In the first regression the probability an innovator keeps the marketing rights of the drug they innovate is estimated as a

[4]This number includes non biotechnology pharmaceuticals

function of innovator and product characteristics using a logistic regression.

$$V^{M}_{i,innovator} = X_i\beta + \epsilon_i \tag{7}$$

Where the distribution of $\epsilon_i$ is assumed to be type 1 extreme value, and $X_i$ are characteristics of the product and innovator.

The dependent variable in Table 7 is a dummy which equals one if the innovator of the drug is currently marketing the drug. An observation is a unique combination of tradename, current marketer, and indication class. The coefficients represent how firm and market characteristics affect the probability the inventor keeps the marketing rights of a product.

There are three main findings from these regressions. First of all, innovators are more likely to market a product after they have already invented other products, which is consistent with the existence of cash constraints on new innovators. Second, logistic results in Table 7 suggest innovators are more likely to enter markets when they are already marketing another product in the same physician specialty. In addition, as the potential market size of a drug increases, the importance that the innovator is already marketing another product in that physician class increases.[5] This is consistent with firms being able to economize on marketing costs by marketing multiple products in the same physician class.

Finally, the results show the level of competition in a market and in a physician class affect the valuation of an innovator from keeping the marketing rights for their innovation. As the number of biotechnology competitors in a market increases, the probability the innovator markets the product decreases. Similarly as the number of other biotechnology products in a physician class increases the probability an innovator markets the product decreases. Surprisingly, the number of non-biotech competitors in a market has no effect on the innovator's probability of marketing a drug.

This regression fails to take into account the valuations of all other potential marketers for a given product which I will do in the next section. From this regression we see that economies of scale at the physician class level, cash constraints faced by new firms, competition at the physician class level and competition at the product market level all seem to affect innovators choice of whether or not to

[5]Market size in these regressions is the ranking of the disease within the physician class (1-5) multiplied by the size of the physician specialty

license their product.

## 5.2 Which firm ends up with marketing rights?

Before presenting my regression estimates I will show summary statistics that display some of the basic patterns in the data. A potential marketer in this section is defined as the innovator of the product as well as any other firm that currently markets any biotechnology pharmaceuticals. Tables 4 and 5 both show summary statistics of firm, product and the interactions between firm and product characteristics. In Table 4 the unit of analysis is an actual observed current marketer, product pair, while in Table 5 the unit of analysis is a potential marketer, product pair. By comparing these two tables we can learn about which variables predict which firm actually markets the product. From Table 4 we see the current marketer of a drug on average markets one other product in the same physician class, while Table 5 shows the average potential marketer markets 0.4 other drugs in the same physician specialty. Comparing these tables also shows the actual marketer of the drug is more likely to also market other products that treat the same disease as the drug. Finally we see that 30% of products are marketed by the innovator of the drug. These tables suggest that a potential marketer is more likely to be the actual marketer of a drug if they innovated the drug, if they are marketing other products in the same physician class, and/or if they are currently marketing other products that treat the same disease.

The next set of regressions examine what characteristics of firms and products predict a high value match; conditional on the location of innovation and the characteristics of a product and potential marketers, I look for predictors of which firm markets the product. Therefore, an observation is a product potential marketer pair, and the regressors are firm characteristics and interactions between firm characteristics and product characteristics and the dependent variable is a dummy which equals one if a firm markets a particular drug.

In the following regressions I assume that the firm with the highest marketing profit from a particular drug markets it. If we assume that a firm's marketing value from marketing drug $i$ is:

$$V_{ij}^{M} = X_{ij}\beta + \epsilon_{ij}^{M} \tag{8}$$

Then if firm $j$ markets product $i$ that implies that $V_{ij}^{M}$ is the maximum among all $J$ firms' profits.

Therefore the statistical model is driven by the probability that firm $j$ markets product $i$:

$$Prob(V_{ij}^M > V_{ij'}^M) \ \forall \ j' \neq j \tag{9}$$

I assume also that $\epsilon_{ij}^M$ is distributed iid type 1 extreme value and condition my estimation on one potential marketing firm marketing each product. Therefore, we have the McFadden choice model where:

$$Prob(Y_i = j) = \frac{e_{ij}^x \beta}{\sum_{k=1}^J e_{ik}^x \beta} \tag{10}$$

My estimation includes a product fixed effect. The characteristics of marketing costs that do not vary across the potential marketing firms of a given product fall out of the probability. Therefore, I cannot identify, for example, the effect of market size on the probability of a firm acquiring a drug but rather only how the effect of market size differentially affects small vs. large firms' probability of acquiring a drug.

The regressors are proxies for why one firm's profit from marketing a drug may be different from another firm's profit from marketing that same drug. In the first column of Table 8, these predictors are the number of other products that a firm markets in a physician specialty and whether or not they were the innovator of the drug. In addition, a dummy which controls for the fact that I do not have information about the portfolios of the large traditional pharmaceutical firms is included.

The second column of table 8, presents the results of repeating the above exercise while adding more covariates. Results from both columns of Table 8 suggest that having other drugs in a physician specialty increases the probability of a firm to market that drug, particularly in large markets. In addition these results suggest having other products in the same indication class increases a firms probability of acquiring a drug, however this effect decreases with the number of other biotechnology products in that indication class. This is consistent with the idea that the incentive to deter entry decreases with the number of other products already in the market.

Similar to the results in the previous innovator regressions, innovators are more likely to keep the products they invent especially as the number of approved products they have innovated increases. This is consistent with the idea that new biotechnology firms face cash constraints keeping them from marketing their early innovations. After a new firm already has a source of cash flow from an approved drug, then these constraints are less binding.

In the regressions in Table 8, I also include a dummy for the large traditional pharmaceutical firms that controls for the fact that I do not have the full portfolios of these firms. The coefficient on this dummy is positive as expected.[6]

From these regressions I find that competitive effects at the physician specialty level and at the product market level seem to be important drivers of the differences in firms profits. In addition these regressions suggest that all other things equal innovators have higher valuation for the products they innovate and that this innovator's advantage increases as the firm has innovated more products. Finally these regressions suggest that firms are able to realize economies of scale in marketing at the physician specialty level.

# 6 Model Estimation

In the previous regressions the rest of the portfolio of a firm is assumed to be exogenous. If we believe a firm makes portfolio decisions jointly across products, this assumption is violated. The next part of the estimation employs a rank based matching estimator that does not require assumptions about the exogeneity of the rest of the portfolio.

In addition, the previous estimation does not fully take into account the rivalrous nature of the product firm match; if one firm markets a product they prevent another firm from marketing that product. Firms may care not only about whether or not they market a product but also who markets the product if they do not; by allowing another firm to enter a market an incumbent firm faces increased competition. In the following estimation I also make the additional assumption that there are no profitable bilateral trades of single products, in addition to assuming there are reallocations of single products.

The next section describes the parametrization of the value function of a firm from marketing a bundle of products and is followed by the empirical estimation strategy. Finally, the estimated parameters of the structural model are presented and used to show how competition in the licensing market varies across physician specialties and indication classes.

[6] All these results do not change qualitatively and change very little quantitatively if instead of a product fixed effect I add a market fixed effect and condition on the number of firms that enter a markets.

## 6.1 Parametrization of the Value Function

Define $V_j^D$ to be the deterministic part of firm $j$'s value from marketing bundle $B_j$ given an industry wide allocation $B$:

$$V_j(B) = V_j^D(B) + \sum_{i \in B} \epsilon_{ij} \tag{11}$$

I label the inherent profitability for a given product $i$ as $\alpha_i$. $I_{ij}$ is a dummy which indicates if firm $j$ innovated product $i$, and I allow the innovator of a drug $i$ to realize cost savings $\theta$ from marketing their own invention. The magnitude of the innovator's advantage is allowed to vary with $H_j$, the number of approved drugs a firm has previously innovated

Again, I allow for two types of competitive effects in my estimation. First of all, firms may face competitive effects in the downstream product market; more competitors in a given indication class $m$ may lower the profits a firm realizes from operating in that market. Therefore, if the number of products in a market is fixed, firms may have an incentive to decrease competition by acquiring multiple products in a given indication class preventing other firms from entering. I therefore allow a firm's value for marketing a drug to decrease log linearly in the number of other firms marketing a product in the same indication class $F^m$.

The second type of competition occurs at the physician class level; as there are more competitive bidders for a given product in a physician class $d$, the split of producer surplus may shift towards the innovator. Hence marketers may have an incentive to acquire multiple drugs in a physician class in order to preserve their future market power in the licensing market. Although this effect is dynamic for now it will enter into the valuation equation a static way. I therefore allow a firm's value for marketing a drug to decrease log linearly in the number of other firms marketing a product in the same physician class, $F^d$.

In addition, a firm $j$'s costs from marketing a bundle of products in a given physician class $d$ is allowed to vary both on the size of the physician class $S_d$ as well as with sizes of the indication classes $S_i$ these products treat. The number of physicians in a physician specialty enters the equation logarithmically. In addition $\gamma$ scales the impact of the size of the physician class on overall marketing costs. If $\gamma$ is estimated to be zero then that would be interpreted as the amount a firm can economize by marketing multiple drugs in the same physician specialty does not depend on the number of

physicians in the physician specialty.

Marketing costs at the physician class level are allowed to increase nonlinearly. I also control for the fact that I do not have the full product portfolios of large traditional pharmaceutical firms by adjusting by their portfolio sizes in all physician classes by a constant to be estimated; $L$ is a dummy which equals one if a firm is a large traditional pharmaceutical firm. In my estimation I also allow for firms to realize decreasing returns to scale in the total number of total products they market $|B_j|$.

The total marketing cost $M$ that a firm $j$ incurs from marketing bundle $B_j$ is:

$$M(B_j) = \sum_{d \epsilon D} (\mu_1((\sum_{i \epsilon B_j} S_i) + \mu_2 L) * log(S_d)^{\gamma}) + \mu_3((\sum_{i \epsilon B_j} S_i) + \mu_2 L) * log(S_d)^{\gamma})^2 \tag{12}$$

If there are economies of scale in marketing then $\mu_3$ should be negative. The total deterministic value firm $j$ has for marketing the bundle $B_j$ given the market-wide allocation $B$ is:

$$V_j^D(B) = \sum_{i \epsilon B_j} (\alpha_i + \theta * I_{ij} + \beta_1 * I_{ij} * H_{ij} - \beta_2 log(F_i^m) - \beta_3 log(F_i^d) - M(B_j) - \beta_4^{|B_j|} \tag{13}$$

Note that neither $\alpha_i$ nor $\mu_1$ can be identified using the estimator suggested above as the effects cancel on each side of the inequalities used in estimation. In addition, there will need to be a normalization of one of the parameters in order to estimate the model. $\theta$ is normalized to be equal to one and the parameters $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, $\mu_2$, $\mu_3$, and $\gamma$ are estimated.

## 6.2 Estimation Strategy

The empirical model is estimated using the set of local pairwise stability inequalities following the methodology presented in Fox 2007.[7] I will find the parameter values which maximize the number of the local pairwise stability inequalities that hold. The statistical consistency of the estimator depends on a non-parametric assumption on the joint distribution of firm product match specific error terms $\epsilon_{ij}$ that I will discuss later.

### 6.2.1 Objective Function

Next I will describe the objective function used in estimation. I assume the observed distribution of products across firms is locally pairwise stable, and will use the revealed choice inequalities implied

[7] Intuitively the estimator finds the parameters that maximize the number of local pairwise stability inequalities that hold given the observed allocation of products across firms without relying on the error term.

by that assumption in my estimation. Recall the set $\Theta^B_{j,j'}$ includes the subset of all partitions of size $J$ of the set of products $I$ where firm $j$ and firm $j'$ switch single products from the allocation $B$ or firm $j$ increases (decreases) the size of its portfolio $B_j$ by one product and firm $j'$ decreases (increases) the size of its portfolio $B_{j'}$ by one product. Looking across all pairs of firms I define $\Theta^B = \bigcup_{j=1}^{J} \bigcup_{j=j+1}^{J} \Theta^B_{j,j'}$. Next I will define the parameter space as $\Omega = \Re^m$ where $m$ is the number of parameters to be estimated, and let $B^*$ to be the observed allocation. $V_j^D(B;\omega)$ is the deterministic value of firm $J$ from allocation $B$ given parameter values $\omega$. In my estimation I find $\omega^*$, where $1[.]$ is an indicator function:

$$\omega^* = \arg\max_{\omega \epsilon \Omega} ( \sum_{B \in \Theta^{B^*}} 1[V_j^D(B^*;\omega) + V_i^D(B^*;\omega) - V_j^D(B;\omega) - V_i^D(B;\omega) > 0]) \tag{14}$$

Note that this function is not smooth and therefore numerical techniques are used to find the parameters which maximize this equation. Following the recommendation of Fox (2007) the method known as differential evolution is employed to find the optimal parameter values.

As mentioned before, using this estimation technique I will be able to identify the relative importance of different covariates on firms' valuations for bundles of products. An attractive feature of this estimator is that any drug specific omitted variables which affect all firms' valuations for that drug equally difference out of the previous inequalities and therefore do not bias the structural parameters. Using this estimation technique implies only effects that vary across allocations can be identified. Therefore, the part of a firm's value which is the same for all firms, the product fixed effect, will not be identified in my estimation.

### 6.2.2 Rank Order Condition and Asymptotics

Statistical consistency rests on the joint distribution of firm $j$ product $i$ match specific error terms $\epsilon_{ij}$ following the rank order condition. The rank order condition implies that for any two allocations $B^{'}$, and $B^{''}$ where one allocation can be obtained by a feasible deviation from the other, the following condition holds:[8]

$$V_1^D(B^{'}) + V_2^D(B^{'}) > V_1^D(B^{''}) + V_2^D(B^{''}) \Leftrightarrow P(B^{'}|X_1...X_J) > P(B^{'}|X_1...X_J) \tag{15}$$

[8] A feasible deviation is defined as one firm sells the marketing rights of one their products to another firm or these two firms trade single products

Where $P$ is the probability to the econometrician that the allocation $B$ is the observed market outcome. The rank order property compares two similar allocations, $B^{'}$, and $B^{''}$. If the local pairwise stability inequalities hold, $B^{''}$ cannot be an stable allocation of the deterministic game, as there exists a deviation which would make two firms better off. In a stochastic game, both $B^{'}$, and $B^{''}$ may occur with positive probability. The local pairwise stability inequalities can be violated at allocations that occur with positive probability. However, as discussed in Fox (2007) when a given inequality is evaluated at the true parameter values an allocation that violates the inequalities is less likely to occur than a nearly identical allocation that satisfies the inequalities. In a game with multiple stable assignments, the rank order property will not hold if the selection rule selects assignment $B^{''}$ more often than $B^{'}$. The equilibrium selection rule cannot work to counteract the signal in the data.

The rank order property may not hold if the idiosyncratic match values are iid across firms and products. However, Fox (2007) and Bajari and Fox (2007) present evidence using Monte Carlo experiments suggesting that the bias imposed by assuming a firm product specific error term which is iid across firms and products is small especially when the number of agents in the market is large.[9] I have also performed several simulations using a simplified framework testing how the assumptions of the variance of the iid error term affect whether or not the rank order condition holds given the actual level of variance in firms' values predicted given my estimated structural parameters. These results are presented in an appendix. This simulation and previous Monte Carlo evidence suggests the assumption that the error terms are iid across firms and products, while does not imply the rank order condition will hold, should impose little if any bias on the estimates.

The asymptotics of the estimator are in the number firms observed in a very large market.[10] Confidence intervals are calculated using subsampling; successive parameter estimates are calculated using subsamples of marketing firms (and their entire product portfolios) drawn without replacement from the observed data. Consistency of this estimator under the previously described assumptions when only using a subset of necessary conditions is shown in Fox (2007). If we are worried that the

[9]If instead we believe the error term is allocation specific and iid across allocations, or if there is a iid shock to each product (constant across firms) then the rank order condition holds.

[10]This asymptotic argument assumes we keep observing more and more firms in the market not that the true size of the market increases. In particular in my application, the literal assumption is the pharmaceutical industry is infinitely large and as I keep observing more and more firms (and their entire product portfolios) in this industry my coefficients will converge to their true values.

allocation we observe in the market is actually determined by a stronger assumption about market outcomes, for example it is in the core, the estimates using the set of inequalities implied by the local pairwise stability assumption are still consistent.

## 6.3 Estimates

In my estimation the set of potential marketers includes any firm that is currently marketing at least one biotechnology pharmaceutical. I do not include innovators who do not market any products as potential marketers as these firms may face constraints that I do not observe. Hence the coefficient $\theta$ on the innovator dummy is interpreted as conditional on a firm being able to market at least one drug, the increase in value the innovator has compared to all other potential marketing firms for that product is $\theta$.

The point estimates with 90% confidence intervals are presented on Table 9. These estimates demonstrate as expected that profits decrease in the number of other firms marketing drugs treating the same indication and also in the number of other firms marketing products in the same physician class. In addition, my estimates show the presence of increasing returns to scale in marketing at the physician class level, and decreasing returns in the total number of drugs a firm markets. The innovator's advantage is the strongest effect determining the location of marketing, especially if the innovating firm already has approved drugs. The model was estimated using several specifications and the results are fairly similar across all specifications. Recall that the estimates are only identified up to a scaling term (the normalization of the coefficient on the innovator dummy $\theta$).

For the second two columns in Table 9, I estimated the model using a subset of inequalities used in the previous estimation, namely only those that result from one firm acquiring a single product from another firm. This estimation uses a substantially smaller number of inequalities for identification and hence my parameter estimates are not as precise. Qualitatively the results are similar.

In Table 10, I present average marginal effects. The values on this table are calculated by first taking the firm specific value (firm specific value excludes the product fixed effect which is not identified) of all potential marketers of a product and comparing that with how much a firm's value would change when product characteristics vary. The values presented in Table 10 are the average change

in values across all potential marketers and all products.

### 6.3.1 Innovator's Advantage

All effects are estimated relative to the magnitude of the innovators advantage. Recall the interpretation of this coefficient is the increase in value an innovating firm has for their invention relative to all other firms conditional on the innovating firm marketing at least one drug. From the point estimates in Table 9 we see that consistent with the logistic regressions, as innovators innovate more products the magnitude of the innovator's advantage increases. This is consistent with new innovators facing cash constraints which are less important as they begin to receive revenues from previously approved products. When looking at Table 10 we see that if we look at the change in value of a firm from marketing a product if they were the innovator versus if they weren't the innovator, the increase in the firm's value is relatively large. This suggests that the innovator's advantage is the most important force in determining the ultimate marketer of a product, particularly when the innovating firm has previously innovated other products. If the innovator faces constraints which keep them from marketing a product they have innovated then other forces will guide which firm ultimately markets the drug.

### 6.3.2 Competitive Effects

Competitive effects play an important role in the allocation of products across firms. As we would expect, keeping firms out of the product market seems to be more important than deterring entry at the physician class level.

### 6.3.3 Economies of Scale

Economies of scale also determine which firm ends up marketing a new innovation. My estimates demonstrate the presence of economies of scale when a firm markets multiple products in the same physician specialty and the importance of these scale economies increases in the size of the physician specialty prescribing the drug. In addition, my estimates show that firm's face diseconomies of scale in the overall number of products in their portfolio.

The point estimate of $\mu_3$, the coefficient on the squared term of the marketing costs, is negative

suggesting firms realize economies of scale when marketing multiple products in the same physician class. The estimate of the physician class scaling term $\gamma$ is positive, suggesting that marketing costs increase in the size of the physician class implying the cost savings of a firm with multiple products in the same physician class versus a firms with fewer other products in the same physician class is larger when the physician class size is larger. $\beta_4$ is greater than one indicating the presence of decreasing returns to scale in the total number of products a firm markets.

## 6.4 Variation in Potential Marketing Firm's Values Across Product Markets

In this subsection I show how potential marketing firms' values for adding a given product to their portfolio varies with characteristics of the product market and physician class. Using the allocative mechanism described in subsection 3.3 as a framework, I consider a new innovation where the innovator of that drug decides to license the marketing rights of this product. Using my parameter estimates I will show how potential marketers' values for that product vary taking the allocation of all other products as fixed.[11]

Figures 7 and 8 show the top ten potential marketers' values for different products. In Figure 7 I show how the distribution of potential marketing firms' values shift with market size (number of patients with the disease the drug treats) of the drug. I compare two drugs in the same physician class that treat different sized patient populations. The y-axis in these graphs measures firms' values for marketing a product net of any product fixed effects. I refer to the value on the y-axis as the firm specific value for a product. Firm specific values increase with the size of the patient population the product treats. This occurs because firms' marketing costs are concave in the firm's presence in a physician specialty. Notice also the difference between the first and second highest bidder is larger in the smaller market again due to the concavity of the cost function.

Figure 8 shows how firms' values for a product vary with the concentration of products across firms in the physician class. In this figure I compare two products which treat the same sized patient population but are in different physician classes. Product A is in a physician class with an Herfindahl-Hirschman Index=.06 (calculated using the distribution of products marketed by any by any firm in

[11]Potential marketer is defined as any firm currently marketing at least one biotechnology drug

my sample within a physician classes). The second product, product B, is in a physician class with HHI=.14. We see in the concentrated physician class the firm with the largest presence in this market has a strong incentive to acquire the product due to their ability to realize economies of scale and their incentive to deter entry by new firms into the physician class. The second highest bidder for product B has a much lower value for acquiring the drug. Therefore, even though the highest bidder for product B has a much higher value for the product than any other bidder for product A, the return to the innovator of product A may be larger in the less concentrated market.[12]

Figures 9 and 10 show how the difference between the potential marketer with the highest value and the second highest value for a product varies with product market attributes. In order to make these next figures, I first calculated each potential marketing firm's value for adding a given product to their portfolio assuming that product is the last product to be allocated. Then I calculated the difference between the potential marketer with the highest value and the second highest value for each product. Next, I took the average of that difference across every product in a given physician specialty. From these graphs we see that the difference in values between the firms with the highest and second highest valuations increase with the HHI of the physician class and the size of the physician specialty. An increase in the size of a physician class by 10,000 physicians increases the difference between the firm with the highest valuation and the firm with the second highest valuation by 2% on average.[13]

### 6.4.1 Interpretation of Results

Recall in section 3.3 that the relationship between the difference in potential marketers' values and the incentives for innovation was discussed. This section explained how in markets where the difference in potential marketers' values was largest, the threat of being help up in the licensing market distorts the incentives for innovation for innovators with low values for marketing the product themselves. My estimates show that the low marketing value innovators are those small startup innovators with no established cash flow and no marketing experience. My results also show small innovators face

[12]The total return also depends on the product fixed effect

[13]This calculation was made by first calculating the difference between the firms with the first and second highest valuation for each product and then recalculating firms valuations assuming there were 10,000 more physicians in every physician class. I then again calculated the difference between the firm with the highest and the firm with the second highest valuation would be for each product. I then looked at the difference before minus the difference after the increase in physician class size by 2000, and divided that difference by the size of the original difference and took the average across all drugs.

the greatest threat of holdup when innovating products that are prescribed by specialties with the most physicians and/or specialties where the distribution of products across marketing firms is most concentrated.

# 7 Conclusions

In this paper, I empirically demonstrate that incentives for innovation are distorted for startup innovators in many large health care markets due to a lack of competition in licensing markets.

Using assumptions about the local pairwise stability of the observed allocation of U.S. marketing rights for biotechnology pharmaceuticals, I analyzed a unique dataset collected from many sources to empirically estimate a structural model of potential marketing firms' profits. I found that there are various factors driving the allocation of products across firms including: a firm's ability to realize economies of scale at the physician class level, competitive externalities at the product market level, and competitive externalities at the physician class level. In addition, my results suggest that innovators have an advantage over other firms in marketing their innovations, all other things equal, and this advantage increases as innovators have another established source of cash flow.

These results have several implications. First, these results explain why as research trends towards drugs treating smaller patient populations innovation increasingly occurs in small startup firms and why these small firms are today more likely than in the past to keep the marketing rights for their innovations. The findings in this paper also suggest that in addition to considering the effects mergers have on competition in the downstream product market, it is also important to consider the effects potential mergers may have on competition in the licensing market. In particular, a merger between two firms that do not compete directly with each other in a given product market but are dominant in a given physician specialty may decrease the competitiveness of the licensing market for new products and therefore skew incentives for future innovation by small firms. The results in this paper suggest that this effect is especially important to consider when merging firms operate in the largest physician specialties.

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# Appendix

# Simulation Results

In the following simulation I look to see how relationship between the variance of an iid firm product random shock, the level of variation in the deterministic variables, and when the rank order condition holds. There is not a proof about what the tradeoff is between the standard deviation of the error term and the standard deviation of the deterministic values of firms for a given product so I have performed some basic simulations to examine this tradeoff given the estimated variance in the deterministic values of firms.

I consider the allocation of three products across three firms without externalities. I find that when the standard deviation of firms' values is comparable to the standard deviation of the error term then the rank order holds. On the other hand, when the standard deviation of the error term is

much larger than the standard deviation of the deterministic values of firms the rank order condition is violated. In my simulation these violations are rare.

My structural estimation suggests the mean standard deviation in firms' values for products is .78. Using this number I first make three draws of a product's value. I repeat this three times. I then have a data set of three firms values for three different products. Using this I can rank all possible allocations in terms of the deterministic values firms have for that allocation. I only consider allocations where each firm has one product. There are 6 possible allocations.

Next I assume the firm product match specific error is distributed normally with mean zero and standard deviation $\sigma$ which I will vary. For a given standard deviation, using 1,000,000 random draws of nine firm product match specific errors, I numerically calculate the probability of each allocation occurring. Next I look to see if the rank order condition holds, that is the deterministic value of a given allocation A is greater than the deterministic value of allocation B if and only if the probability of allocation A is greater than the probability of allocation B.

For each value of $\sigma$ I repeat the above process 5 times for 5 different draws of deterministic product values. The values of $\sigma$ I use are: .78, 1.5 and 8. I find that for all 5 draws of product values the rank order condition holds when $\sigma$ is equal to .78 and 1.5. When $\sigma$ is equal to 8 the rank order condition holds 4 out of 5 times and is only violated when deterministic product values are very close.

# Tables and Figures

Table 1: Outcomes of Biotechnology Pharmaceutical Innovators with 1+ Approved Drugs

| Firm Status | Number of Firms |
|---|---|
| Operating | 31 |
| Acquired | 34 |
| Merged | 7 |
| Bankrupt | 1 |
| *Total* | *73* |

Firm Status in July 2006 of 73 (out of 100 total) Innovators of Approved Biotechnology Pharmaceutical Drugs. Firm status information comes from company websites, press releases, and Recombinant Capital Database.

Table 2: Number of Approved Biotech Pharmaceuticals Successful Innovators Control Marketing Rights for at time of Merger or Acquisition

| Number of Products | Firms |
|---|---|
| 0 | 14 |
| 1 | 17 |
| 2 | 5 |
| 3 | 3 |
| 4 | 2 |
| *Total* | *41* |

Sample of firms are the 41 innovators with at least 1 approved biotechnology drugs (out of 73 total innovators information was available for -Table 1) who either merged or were acquired by another firm prior to July 2006. Information comes from press releases and company 10-k reports.

Table 3: Number of Indications treated per tradename

| Indications Treated | Tradenames |
|---|---|
| 1 | 67 |
| 2 | 67 |
| 3 | 7 |
| 4 | 6 |
| 5 | 1 |
| 6 | 1 |
| *Total* | *149* |

Information comes from Physician Interviews and FDA website. An indication is defined as a particular condition that the drug treats ex. rheumatoid arthritis.

Table 4: Summary Statistics: Product Level

| Variable | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|
| The innovator is the current marketer of the drug | 0.3 | 0.46 | 0 | 1 |
| Number of other products current marketer also markets that are prescribed by physicians in the same physician specialty | 0.89 | 1.29 | 0 | 6 |
| Number of other products current marketer also markets treating the same disease | 0.25 | 0.68 | 0 | 5 |
| Relative size of patient population with the disease the product treats within physician specialty | 3.14 | 1.5 | 1 | 5 |
| Number of physicians in the physician specialty that prescribes the drug | 21,425 | 27,726 | 2,452 | 99,913 |
| Log(Relative disease size within Phy. Specialty * Physician Specialty Size) | 10.46 | 1.02 | 7.8 | 13.12 |
| Number of other Biotech Products treating the same disease | 1.18 | 1.18 | 0 | 4 |
| Controls for Non-Biotech Products treating the same disease | 1.2 | 0.2 | 0 | 3 |
| Large Traditional Pharmaceutical firm currently markets the drug | 0.15 | 0.36 | 0 | 1 |
| Observations=294 | | | | |

Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. Drugs were classified into physician specialties and disease/indication classes through physician interviews.

Table 5: Summary Statistics: Potential Marketer ∗ Product Level

| Variable | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|
| Potential marketer was the innovator of the drug | 0.014 | 0.120 | 0 | 1 |
| Number of other products potential marketer also markets that are prescribed by physicians in the same physician specialty | 0.39 | 0.86 | 0 | 6 |
| Number of other products potential marketer also markets treating the same disease | 0.022 | 0.180 | 0 | 5 |
| Relative size of patient population with the disease the product treats within physician specialty | 3.14 | 1.50 | 1 | 5 |
| Number of physicians in the physician specialty that prescribes the drug | 21,418 | 27,672 | 2,452 | 99,913 |
| Log(Relative disease size within Phy. Specialty * Physician Specialty Size) | 10.46 | 1.02 | 7.8 | 13.12 |
| Number of other Biotech Products treating the same disease | 1.18 | 1.18 | 0 | 4 |
| Controls for Non-Biotech Products treating the same disease | 1.20 | 0.82 | 0 | 3 |
| Large Traditional Pharmaceutical firm currently markets the drug | 0.12 | 0.31 | 0 | 1 |
| *Observations=20,448* | | | | |

Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. A potential marketer is defined as any firm currently marketing at least one biotechnology pharmaceutical or is the innovator of the product. An observation is a potential marketer, product combination. Drugs were classified into physician specialties and disease/indication classes through physician interviews.

Table 6: Summary Statistics: Disease Class

| Variable | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|
| Relative size of patient population with the disease the product treats within physician specialty | 3.03 | 1.49 | 1 | 5 |
| At least one drug that treats the disease is marketed by the innovator of that drug | 0.42 | 0.50 | 0 | 1 |
| At least one large traditional pharmaceutical firm is marketing a product treating the disease | 0.24 | 0.43 | 0 | 1 |
| Number of other Biotech Products treating the same disease | 0.76 | 1.05 | 0 | 4 |
| Controls for Non-Biotech Products treating the same disease | 1.20 | 0.81 | 0 | 3 |
| *Observations=182* | | | | |

Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. An observation is as an disease/indication class. Drugs were classified into physician specialties and disease/indication classes through physician interviews.

Table 7: Logistic Regression: Innovators Probability of Marketing their Innovation: *Excludes products innovated by Large Pharma*

| Innovator Keeps Product | dy/dx | Std. Error | P>\|z\| |
|---|---|---|---|
| *Cash Constraints* | | | |
| Number of Products with FDA Approval Firm previously Innovated | 0.014 | 0.010 | 0.15 |
| *Market Size= Size of Physician Specialty*Relative Market Size* | | | |
| Log of the Size of the Market | -0.017 | 0.030 | 0.57 |
| *Scale Economies* | | | |
| Number of other Products Firm Markets in the same Physician Class | 0.08 | 0.04 | 0.08 |
| Firm markets at least one other product in same Physician Class * Log(Market Size) | 0.03 | 0.01 | 0.00 |
| *Competition* | | | |
| Number of Other Biotech Products in Indication Class | -0.049 | 0.026 | 0.06 |
| Controls for Non Biotech Products in Indication Class | 0.04 | 0.03 | 0.25 |
| Number of other Biotech Products in Physician Class | -0.004 | 0.001 | 0.02 |
| *Observations=288* | | | |

Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. An observation is a product. Products innovated by large pharmaceutical firms are excluded from the regression.

Table 8: Conditional Logit Estimates

| Firm and Product Match | Odds Ratio | Std. Error | Odds Ratio | Std. Error |
|---|---|---|---|---|
| *Innovator Advantage* | | | | |
| Firm is the Innovator | 36.87 | (5.05) | 15.74 | (3.09) |
| Firm is Innovator * Number of Previously Innovated Products with FDA approval | | | 1.23 | (0.06) |
| *Scale Economies* | | | | |
| Number of other Products Firm also markets in same Physician Class | 1.55 | (0.07) | 1.16 | (0.11) |
| Firm markets at least one other product in same Physician Class * Log(Market Size) | | | 1.06 | (0.03) |
| Firm is Large Traditional Pharma | 2.07 | (0.35) | 2.08 | (0.35) |
| *Competition* | | | | |
| Number of other Products Firm also markets in same Indication Class | | | 2.92 | (0.69) |
| Firm markets at least one other product in Indication.* Number of Other Biotech Products in Ind. | | | 0.75 | (0.13) |
| Firm markets at least one other product in Indication * Controls for Non-Biotech Products in Ind. | | | 1.20 | (0.32) |
| *Observations=20,448* | *$R^2$=0.20* | | *$R^2$=0.24* | |

Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. A potential marketer is defined as any firm currently marketing at least one biotechnology pharmaceutical or is the innovator of the product. An observation is a potential marketer, product combination. The regression includes product level fixed effects, and is conditioned on only one of the potential marketing firms marketing the product. The table presents odds ratios, that is the interpretation of a coefficient on a variable A equal to X is: the odds of being the marketer of the drug given a change in the characteristic A are X times as large than before the change.

Table 9: Market Allocation Estimates

| Firm Value Function Parameter | Coeff | 90% Conf. Int. | Coeff | 90% Conf. Int. | Coeff | 90% Conf. Int. | Coeff | 90% Conf. Int. |
|---|---|---|---|---|---|---|---|---|
| *Innovators Advantage* | | | | | | | | |
| Innovator Dummy -Normalization - θ | 1 | | 1 | | 1 | | 1 | |
| # of approved drugs innovator previously innovated - $\beta_1$ | 0.582 | [ 0.332, 0.772 ] | 0.669 | [ 0.278,0.755 ] | 0.1106 | [ 0.0318, 0.4517 ] | 0.5642 | [0 .142,0.567 ] |
| *Scale Economies* | | | | | | | | |
| Dummy for Large Traditional Pharma - $\mu_2$ | 5.35 | [ -3.27, 11.85 ] | 3.30 | [ -0.71,7.56 ] | 53.23 | [ 8.29, 109.35 ] | 28.204 | [7.24,32.11] |
| (Marketing Costs Scaled by Indication Size) $^2$ - $\mu_3$ | -0.00012 | [-0.0002, 0.0000] | -0.00002 | [-0.0002,-0.00001] | -0.000041 | [-0.0010, -0.0000] | -0.000176 | [-0.0009,-0.0000] |
| Log(Physician Class Size) Scale - γ | 0.059 | [ 0.023, 0.242 ] | 0.396 | [ 0.098,0.511 ] | 0.111 | [ 0.044, 6.09 ] | 1.325 | [ 0.325,8.06 ] |
| Firm Diseconomies - $\beta_4$ | 1.11 | [ 1.05,1.19 ] | 1.13 | [ 1.06,1.15 ] | 1.100 | [ 1.03,1.13 ] | 1.084 | [1.03,1.13] |
| *Competition* | | | | | | | | |
| Log(Number of Other Firms in Indication Class) - $\beta_2$ | -0.041 | [- 0.1382, -0.0061] | -0.041 | [-0.0949,-0.0145] | -0.078 | [ -0.492, -0.029 ] | -0.09 | [ -0.464,-0.040 ] |
| Log(Number of Other Firms in Physician Class) - $\beta_3$ | -0.026 | [-0.0976, 0.0124] | | | -0.165 | [ -11.92, 0.86 ] | | |
| *Inequalities Used in Estimation* | *Single Product Portfolio Inc/Dec & Trades of Single Products* | | | | *Single Product Portfolio Inc/Dec Only* | | | |
| *% of Inequalities Correctly Predicted* | *84.13%* | | *84.06%* | | *79.18%* | | *79.14%* | |

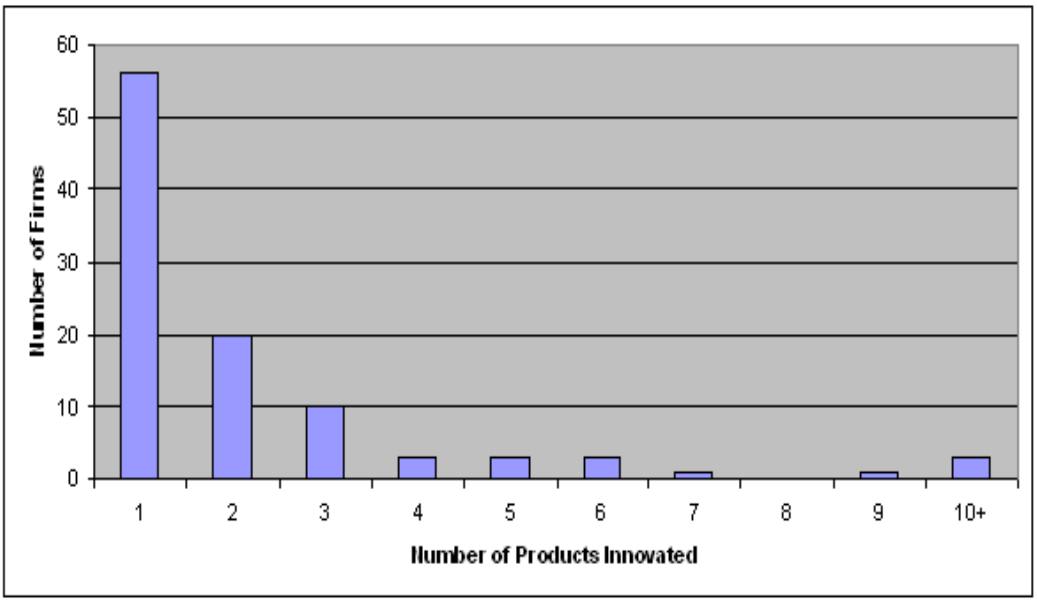
90% Confidence Intervals are presented and were calculated using subsampling by firm product portfolio. Subsampling uses 300 replications, 40 firm portfolios per replication and a convergence rate of $\sqrt{firms}$, as found by Sherman (1993). Data comes from physician interviews, Recombinant Capital Database, as well as from the FDA, company and the AMA website. A product is defined as a current marketer, tradename, indication class combination. A potential marketer is defined as any firm currently marketing at least one biotechnology pharmaceutical. Estimation uses rank based matching estimator Fox (2007).

Table 10: Average Marginal effects

| Variable | Average Change in Potential Marketers' Values for Acquiring Product |
|---|---|
| Increasing Physician Class Portfolio Size by three Average Sized Products | 0.010 |
| Increasing Competition in Physician Class by one firm | 0.014 |
| Increasing Compeition in Indication Class by one Firm | 0.015 |
| Innovator Advantage | 1.000 |
| Increasing # of Products Firms Previously Innovated by 1 (if Innovator) | 0.582 |
| Average Firm Specific Value | -0.50 |

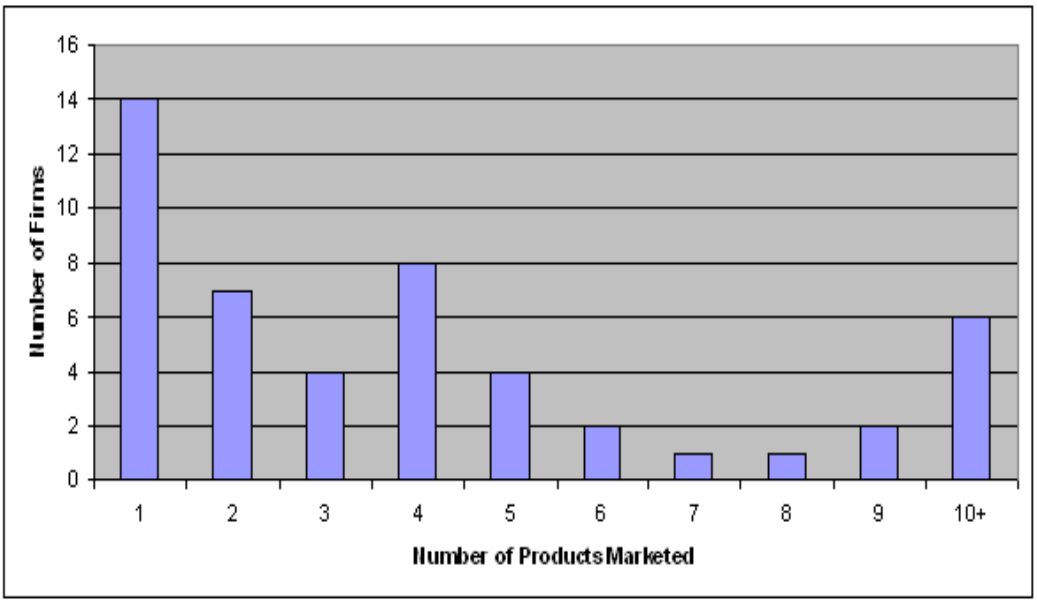
Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. A potential marketer is defined as any firm currently marketing at least one biotechnology pharmaceutical. Estimation uses a rank based matching estimator where the inequalities used in estimation come from the assumption of the local pairwise stability of the observed allocation -inequalities used in estimation include firms making trades of single products or firms adding (decreasing) the size of their portfolios by one product. Average marginal effects are calculated using full estimation (8 parameters). Firm specific value is the marginal value a firm has for a product minus a product fixed effect ($\alpha_i$ and the linear part of the cost function). Values on the table are calculated by first for every product calculating the change in firms specific value every potential marketing firm would experience by changing a given characteristic of the firm or product. Then the average of these values are calculated.

Figure 1: Size Distribution of Innovators



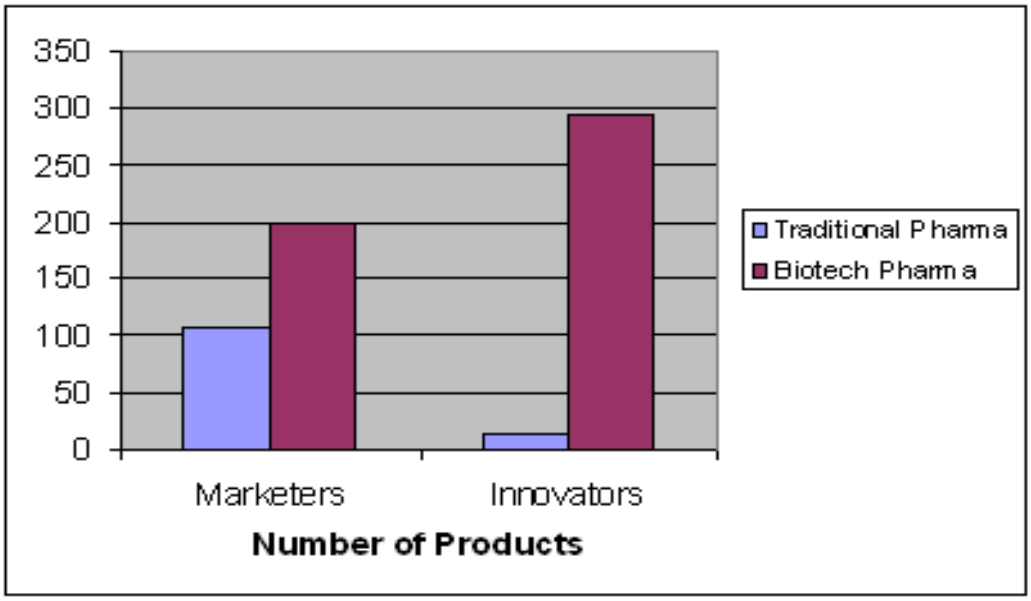

Data comes from company websites, and Recombinant Capital database. A product is defined as a current marketer, tradename, indication class combination. The innovator is defined as the firm which had control of marketing rights when the product entered phase 1 FDA trial.

Figure 2: Product Portfolio size of Marketing Firm: *Excluding large traditional pharmaceutical firms*



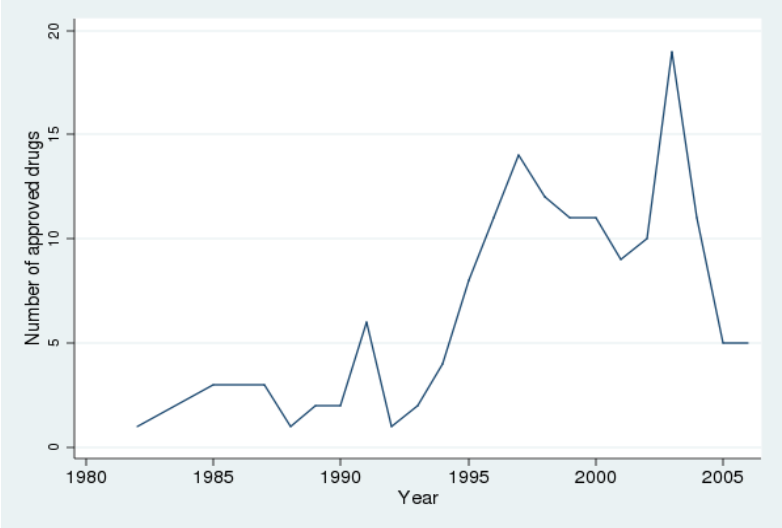

Data comes from company websites, and Recombinant Capital database. A product is defined as a current marketer, tradename, indication class combination. A marketing firm is defined as a firm who had control of US marketing rights in July 2006 of at least one biotech product. Their product portfolio is all of the products they market in the US in July 2006.

Figure 3: Innovation and Marketing by Biotech and Traditional Pharmaceutical Firms




Data comes from company websites, and Recombinant Capital database. A product is defined as a current marketer, tradename, indication class combination. The innovator is defined as the firm which had control of marketing rights when the product entered phase 1 FDA trial. The marketer is defined as the firm who had control of US marketing rights in July 2006.

Figure 4: Yearly FDA Approval of Biotech Pharmaceuticals

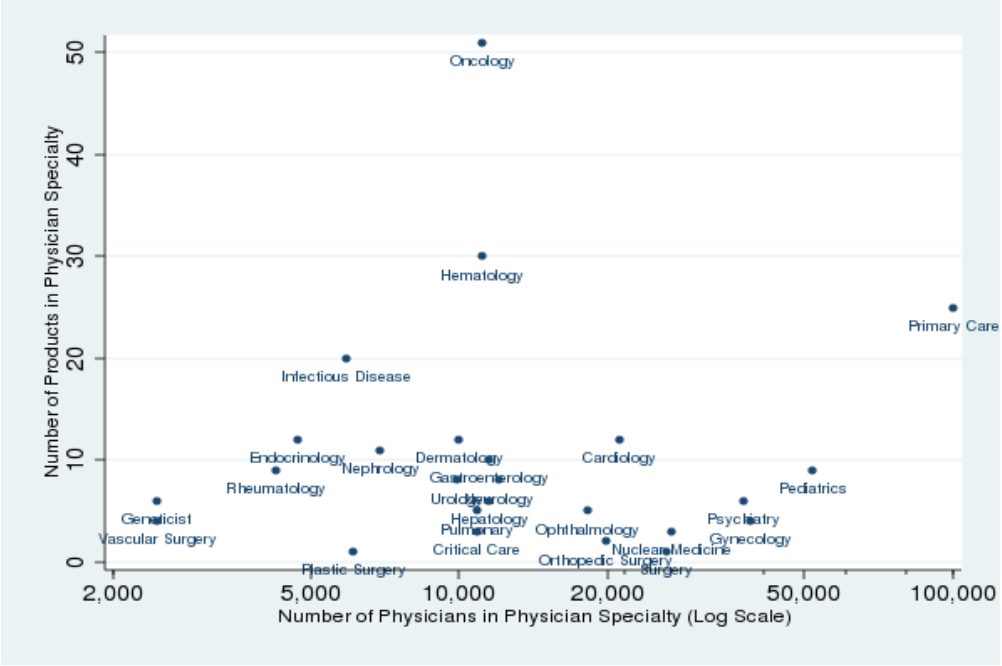



Data comes from FDA website. Approval date is the first date a tradename was approved for any indication by the FDA.

Figure 5: Histogram: Distribution of Products across Indication Classes

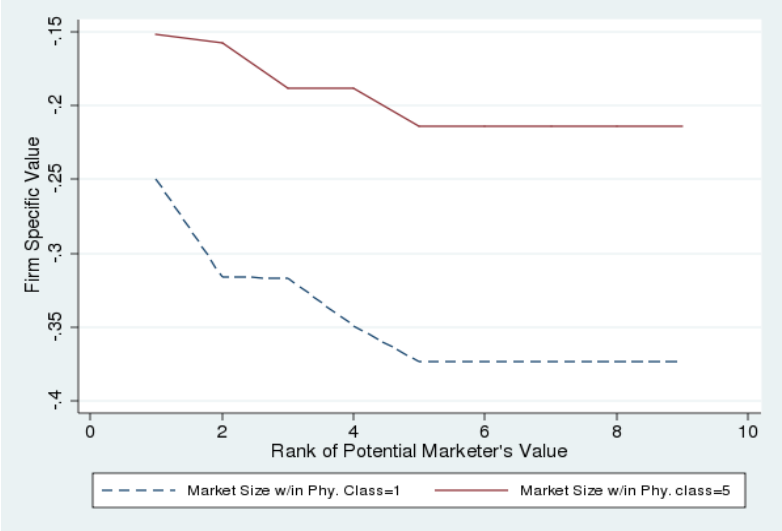

Data comes from physician interviews, FDA website, AMA website, Micromedex, and Uptodate. Which products treat the same indications was verified though physician interviews. All products marketed by any firm (excluding large traditional pharmaceutical firms) currently marketing at least one biotechnology pharmaceutical are included in this figure. Other treatments for a given indication not marketed by a firm in my sample are not included. Drugs in the same indication/disease class compete with one another to be prescribed by a physician when a patient has a particular disease or disorder.

Figure 6: Physician Class Size: *Number of Physicians and Number of Products*



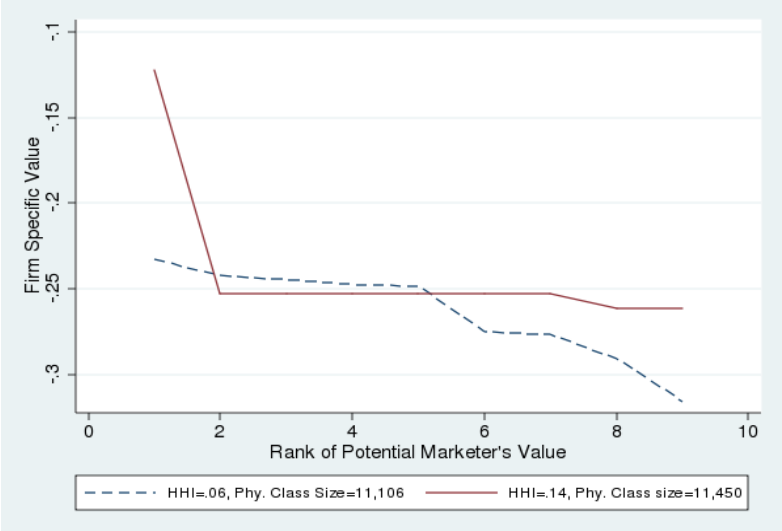

Data comes from physician interviews, FDA website, AMA website, Micromedex, and Uptodate. A product is defined as a current marketer, tradename, indication class combination. The indications that a product are prescribed for were classified into the physician specialties which typically treat the indication through interviews with physicians. All products in any firm in my sample's portfolio (excluding non-biotech products marketed by large traditional pharmaceutical firms) are included in this figure.

Figure 7: Potential Marketer's Value for Acquiring New Product: Variation in Market Size



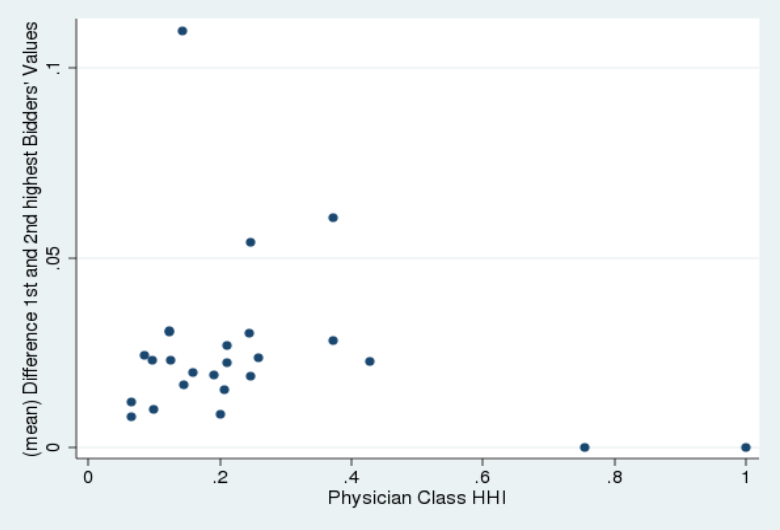

Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. A potential marketer is defined as any firm currently marketing at least one biotechnology pharmaceutical. Firm specific value is the marginal value a firm has for acquiring a product from the current marketer minus a product fixed effect ($\alpha_i$ and the linear part of the cost function). For every potential marketer of each product the firm specific value of the potential marketer for adding the product to their portfolio is calculated taking the allocation of the rest of the products industry as fixed. Parameter values used to calculate firms specific values were estimated using full rank based matching estimation (8 parameters).

Figure 8: Potential Marketer's Value for Acquiring New Product: Variation in Physician Class Concentration




Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. A potential marketer is defined as any firm currently marketing at least one biotechnology pharmaceutical. Firm specific value refers to the marginal value a firm has for acquiring a product from the current marketer minus a product fixed effect ($\alpha_i$ and the linear part of the cost function). For every potential marketer of each product the firm specific value of the potential marketer for adding the product to their portfolio is calculated taking the rest of the products in the firms' portfolio as fixed. Parameter values used to calculated firms specific values were estimated using full rank based matching estimation (8 parameters). HHI is calculated using the distribution of all the products marketed by any firm in my sample in a physician class weighting their market presence by the relative market size of the drugs within that physician class.

Figure 9: Average difference between 1st and 2nd Firm's Value for Acquiring Product: Sorted by Physician Class Concentration




An observation this graph is a physician class. Each point represents the average difference between the highest and second highest potential marketer's value for adding a product in that physician class to their current portfolio. Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. A potential marketer is defined as any firm currently marketing at least one biotechnology pharmaceutical. Parameter values used to calculated firms values were estimated using full rank based matching estimation (8 parameters). Each potential marketer's value for adding each product was calculated and the difference between the firms with the first and second highest valuation was calculated. The mean of this value across all products in the physician class was then calculated.

Figure 10: Average difference between 1st and 2nd Firm's Value for Acquiring Product: Sorted by Physician Class Size


An observation this graph is a physician class. Each point represents the average difference between the highest and second highest potential marketer's value for adding a product in that physician class to their current portfolio. Data comes from physician interviews, Recombinant Capital Database, the FDA website, company websites and the AMA website. A product is defined as a current marketer, tradename, indication class combination. A potential marketer is defined as any firm currently marketing at least one biotechnology pharmaceutical. Parameter values used to calculated firms values were estimated using full rank based matching estimation (8 parameters). Each potential marketer's value for adding each product was calculated and the difference between the firms with the first and second highest valuation was calculated. The mean of this value across all products in the physician class was then calculated.