Abstract

The paper examines the behavior of pharmaceutical incumbents in the period just before they lose patent protection. Because the strategic incentive to deter entry is absent in markets which are so small or large as to make entry deterrence unnecessary or impossible, it is proposed that one way to look for evidence that firms are influenced by a desire to deter entry is to investigate whether behavior is nonmonotonic in the size of the market. The data contain advertising, product proliferation and pricing information for a sample of drugs which lost patent protection between 1986 and 1992. Among the findings consistent with an entry deterrence model are that incumbents in markets of intermediate size are the most likely to reduce detail advertising and to increase the proliferation of presentations in the year before patent expiration.

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Strategic Entry Deterrence and the Behavior of Pharmaceutical Incumbents Prior to Patent Expiration

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1 Introduction

Prior to 1984 all but the most popular drugs tended to retain their monopoly position long after their patent protection expired. FDA regulations required any firm wanting to produce a generic substitute to repeat the lengthy process of tests and clinical trials to which the incumbent had been subjected before being allowed to compete. Things changed dramatically in the mid-1980’s: the Waxman-Hatch Act (1984) greatly reduced regulatory barriers to generic entry and with the proliferation of state laws mandating/allowing generic substitution by pharmacists it became common for generics to earn a majority market share shortly after entry. In this paper, we explore how pharmaceutical incumbents have dealt with the threat of entry. In particular, using a panel of drugs that lost patent protection between 1986 and 1992 we describe patterns in advertising, product proliferation and pricing, and look for evidence that incumbents may have strategically distorted these “investments” in an attempt to deter generic entry.

A large number of theoretical papers have described how firms may make “strategic” investments in capacity, advertising, capital structure, contractual practices, etc., to deter (or accommodate) the entry of potential competitors. The nature of strategic investment models makes them difficult to test directly, however, and relatively little evidence has appeared. The approach we take in looking for evidence of strategic intent is to try to exploit the fact that the incentive to deter entry will typically be larger in intermediate-sized markets than in markets which are sufficiently small/large so that entry deterrence is unnecessary/impossible.

We begin in section 2 with a discussion of strategic investment models meant to help clarify this point. Using a stochastic model which is only slightly different from the textbook three-stage model, we first review what is meant by a “strategic” investment and note why direct tests of strategic intent are difficult. We next point out that, absent entry-deterrence motivations, equilibrium investment levels in some models will be monotonically related to the attractiveness of the market to potential entrants. We then introduce the entry deterrence motivation, discuss why it tends to be largest in intermediate sized markets, and illustrate how this can lead to nonmonotonic patterns in investment levels.

The pharmaceutical industry provides a nice opportunity to study entry deterrence. Looking at

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drugs with expiring patents, one can construct a sizable sample of similarly situated incumbents facing a threat of entry. The available data allow us to look at how firms use a number of potential strategic tools, including two types of advertising, the number of forms in which a drug is sold, and prices. An nice additional feature of the industry is that entry becomes possible at a known patent expiration date. This fact allows us to look for evidence of strategic distortions not only by looking at cross-sectional patterns in investment levels, but also by looking at how investments change over time as patent expiration dates approach.

A necessary precursor to an examination of how incumbent behavior varies with the attractiveness of a market to potential entrants is a measure of market attractiveness. We thus begin by estimating a model of generic entry. Following Grabowski and Vernon (1992) and Scott Morton (1995), we use pre-expiration revenues and other market characteristics to explain a dependent dummy variable for whether generic entry occurs within three years of patent expiration. Generic entry occurs for about 60 percent of the drugs in our sample. The model’s predictions are sufficiently strong so as to allow us to classify a number of drugs as being unlikely or very likely to face entry. This will allow us to compare the behavior of a group of incumbents for which entry deterrence is not a concern with the behavior of incumbents facing an intermediate probability of entry.

Advertising plays an important role in pharmaceutical markets—an oft-cited statistic by critics of the pharmaceutical industry is that more money is spent by the industry on marketing than on research and development.2 Our empirical analysis focuses on the question of whether advertising levels are unusual in “intermediate” markets. We do this in two ways: looking cross-sectionally at advertising to sales ratios, and looking at how advertising is changed immediately prior to patent expiration. One finding consistent with an entry deterrence motivation is that incumbents in intermediate markets are more likely to reduce advertising over that pre-expiration period than are incumbents in markets with a high or low entry probability.

Many prescription drugs are sold in a large number of presentations. The tranquilizer Haldol,

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2See U.S. Congress, Office of Technology Assessment (1993). Bill Clinton, in a 1993 speech, said that the pharmaceutical industry spends “$1 billion more each year on advertising and lobbying than it does on developing new and better drugs . . . . We cannot have profits at the expense of our children.” (The Wall Street Journal, February 16, 1993) Schweitzer (1997) provides a thorough discussion of research and marketing expenditures of pharmaceutical firms. See Caves, Whinston, and Hurwitz (1991), Hurwitz and Caves (1988), Leffler (1981), and Berndt, Bui, Reilly, and Urban (1995) for discussions of other aspects of pharmaceutical advertising.
for example, is sold in $\frac{1}{2}$, 1, 2, 5, 10 and 20 milligram tablets, as a concentrated liquid in bottles, and as a solution for intravenous use in vials, ampules and disposable syringes. While we have seen little written about presentation proliferation as a strategic tool, an industry source we consulted mentioned line extensions as the first thing that would come to mind when one began to plan for generic entry. One possibility is that by increasing the variety of presentations sold, an incumbent would increase the cost to an entrant of reproducing the product line and might thereby deter entry. After presenting some summary statistics on the typical levels of and trends in presentation proliferation, we look at how presentation proliferation varies with the likelihood of generic entry. Again, we do this in two ways: looking at how a Herfindahl index of presentation by presentation revenues varies across drugs, and looking at which drugs are tending to increase proliferation as their patent expiration dates approach.

The final strategic variable we examine is incumbents’ prices. Here, we discuss how prices change before and after patent expiration for drugs with low, medium, and high predicted probabilities of entry in the drugstore and hospital markets.

Our paper can be seen as related to two empirical literatures. First, a number of papers have previously explored pricing, advertising, and entry in the pharmaceutical industry. Most closely related to our work is Caves, Whinston, Hurwitz (1991), a descriptive study based on thirty drugs with patents expiring between 1976 and 1987. They look mostly at average behavior of incumbents before and after expiration, although they do separate drugs into low and high revenue categories and see if incumbent advertising behavior differs. Scott Morton (1995) focuses on the determinants of generic entry with a data set similar to ours. In addition to looking at exogenous market characteristics, she also looks for effects of incumbents’ advertising expenditures on the probability of generic entry. Grabowski and Vernon (1992) also study a panel of drugs with expiring patents and focus on post-entry behavior of both incumbents and generic entrants.

Second, a number of papers have examined strategic entry deterrence (and entry accommodation) in other environments. As we mentioned above, it is difficult to test directly whether

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3In addition to references mentioned above, see Masson and Steiner (1985), Comanor (1986) and Frank and Salkever (1997) for discussions of pharmaceutical prices.

4Some notable papers in addition to those mentioned above are Caves, Whinston, and Hurwitz (1991), Grabowski and Vernon (1990), Scott Morton (1995), Griliches and Cockburn (1994), Frank and Salkever (1992), and Ellison, Cockburn, Griliches, Hausman (1997). There are a number of books of interest about the economics of pharmaceuticals including Walker (1971), Schwartzman (1976), Temin (1980), and Schweitzer (1997).
particular investments are strategic. The one paper we are aware of which has tried this is Kadiyali (1996), a study of the market for film, which estimates price and advertising elasticities and argues that observed levels of price and advertising by Eastman Kodak were inconsistent with static monopoly profit maximization but consistent with entry deterring behavior. Smiley (1988) reports evidence from surveys of firms about what strategies they use to deter entry. In practice, it has been more common to provide indirect evidence that investments are chosen strategically by showing that investments do affect future competition (which will lead us to conclude that investments must be strategic if we believe that firms are rational and aware of the effect on competition). One can think of Chevalier’s (1995a, 1995b) studies of the effect of capital restructuring on entry and exit and supermarket pricing, Lieberman’s (1987) discussion of the responses by incumbents in chemical industries to rivals’ additions of capacity, and Scott Morton’s (1995) discussion of the effects of advertising on entry as providing evidence of this sort. Lieberman also looks for evidence of entry deterring behavior in cross-sectional patterns in examining whether there is more excess capacity in markets which are more concentrated.

The organization of this paper is as follows. Section 2 discusses entry deterrence and the monotonicity of the investment-market size relationship. Section 3 describes our data. Section 4 presents the probit model with which we estimate the likelihood of generic entry. Evidence on advertising is in Section 5; presentation proliferation is in Section 6; and pricing is in Section 7. Section 8 concludes.

2 Strategic entry deterrence

In this section we discuss why it is difficult to test directly whether investments are “strategic” and then describe an idea for how one might look for evidence of strategic entry deterrence by looking for nonmonotonicities in the relationship between incumbents’ actions and the attractiveness of the market to potential entrants.

2.1 A model: definitions and difficulties

In this subsection we sketch a typical model of “strategic investment,” and describe why testing directly whether an investment is strategic is a difficult empirical task.
The prototypical model of strategic investment is a three-stage game like that shown above. In the first stage \((t = 1)\), the incumbent firm (firm 1) chooses an investment level \(A\) at a cost of \(c(A)\). Assume that \(c'(A) > 0\) and \(c''(A) \geq 0\). In the second stage \((t = 2)\), the potential entrant (firm 2) observes the incumbent’s choice of \(A\) and then chooses whether or not to enter the market, which requires paying a sunk cost of \(E\). In a slight departure from the way strategic investment models are usually presented, we will assume that the entry cost \(E\) is stochastic with CDF \(F(E)\), and that the true value is revealed to the potential entrant between the first and second stage. In the third stage \((t = 3)\), either the incumbent is a monopolist or the incumbent and entrant compete as duopolists. If the incumbent is a monopolist, assume that it chooses some action \(x_1^m(A)\) in the third period and as a result earns profits, \(\pi_1^{m*}(A) \equiv \pi_1(x_1^m(A), A)\). If entry occurs, assume that the unique Nash equilibrium of the third stage game involves the firms choosing actions \(x_1^*(A)\) and \(x_2^*(A)\) and receiving profits \(\pi_1^{d*}(A) \equiv \pi_1^d(x_1^*(A), x_2^*(A), A)\). Assume that \(\pi_1^{m*}(A)\) and \(\pi_1^{d*}(A)\) are concave, and that the firms’ best responses are always interior and given by the unique solution to the first-order conditions.

In this model, the incumbent’s investment decision is said to be “strategic” in that firm 1 typically distorts its investment level \(A\) away from the level which maximizes profits (holding subsequent actions fixed) in order to affect the behavior of firm 2. More precisely, we call an investment strategic if the equilibrium value of \(A\) differs from that which would have been chosen in a model where firm 2 did not observe firm 1’s choice of \(A\). In our model, when firm 1 chooses investment level \(A\) its expected profits are given by

\[
E(\pi_1(A)) = F(\pi_2^{d*}(A))\pi_1^{d*}(A) + (1 - F(\pi_2^{d*}(A)))\pi_1^{m*}(A) - c(A).
\]

The first order condition giving firm 1’s equilibrium investment level \(A^*\) is then

\[
c'(A^*) = F(\pi_2^{d*}(A^*))\frac{\partial \pi_1^{d*}}{\partial A}(x_1^*, x_2^*, A^*) + (1 - F(\pi_2^{d*}(A^*)))\frac{\partial \pi_1^{m}}{\partial A}(x_1^m, A^*)
\]
\[ + F(\pi_2^d(A^*)) \frac{\partial \pi_1^d}{\partial x_2} (x_1^*, x_2^*, A^*) \frac{dx_2^*}{dA}(A^*) \]
\[ + (\pi_1^d(A^*) - \pi_1^m(A^*)) \frac{d\pi_2^d}{dA}(A^*) f(\pi_2^d(A^*)) , \]
where we have written \( x_1^* \) and \( x_1^m \) for \( x_1^*(A^*) \) and \( x_1^m(A^*) \) to save space. In contrast, if firm 1’s investment level were unobservable, the first order condition giving the optimal investment level, \( A^u \), would just be

\[ c'(A^u) = F(\pi_2^d(A^u)) \frac{\partial \pi_1^d}{\partial A}(x_1^u, x_2^u, A^u) + (1 - F(\pi_2^d(A^u))) \frac{\partial \pi_1^m}{\partial A}(x_1^m(A^u), A^u) , \]

where \( x_1^u \) and \( x_2^u \) are the equilibrium choices in the third stage of that model.

The difference between the two first order conditions is the presence of the third and fourth terms when \( A \) is observable. The third term is the “strategic entry accommodation” effect. Conditional on firm 2 entering, firm 1 will be better off if its investment has caused firm 2 to alter its action in the direction which increases firm 1’s profit. The fourth term is the “strategic entry deterrence” effect. Because firm 1’s profit is higher when it is a monopolist, it has an incentive to distort its investment in the direction of reducing firm 2’s profit (which reduces the likelihood of firm 2 entering).

The most direct method for testing whether a particular investment is strategic would be to evaluate the terms in the expression above to test which first order condition holds. This, however, will usually be extremely difficult in practice. Entry deterrence can only occur when investments have long term consequences. In real world markets where entry deterrence is a possibility there will typically also be uncertainty about entrants’ plans. As the first order conditions make clear, assessing directly whether an investment is strategic will require estimates not only of the long run elasticity of profits with respect to the investment, but also of the incumbent’s prior on the likelihood of entry and of what the long run benefit of the investment would have been in the counterfactual state of the world where entry had/had not occurred. Carrying out such calculations to any precision will typically be very difficult.

2.2 Monotonicity of investment absent strategic entry deterrence

In this section we discuss how investment levels might be expected to vary in a cross section of markets when investment serves no role in deterring entry. In particular, we discuss conditions
under which investment levels will be monotone in a parameter which reflects the attractiveness of the market to potential entrants.

### 2.2.1 A proposition

Consider a model identical to that of the previous section, but with the additional feature that the profit and cost functions depend also on a characteristic \( z \) of the market, e.g., the number of potential consumers in the market. Assume that the variable \( z \) is normalized so that larger values of \( z \) correspond to markets which are more profitable for firm 2, i.e., \( \frac{\partial}{\partial z} \pi_2^* (A, z) > 0 \). To provide some background for our later discussion of the potential of strategic entry deterrence to create nonmonotonic investment patterns, we focus in this section on a model in which no entry deterrence effects are present. In particular, we consider firm 1’s choice of an investment level when the investment choice is revealed to firm 2, but only after firm 2 has made its entry decision. (Note that as a result investment levels in this section will reflect entry accommodation motivations.)

In this model, we think of investment levels as changing with \( z \) for two reasons. First, we refer to \( F(\pi_2^*) \frac{\partial^2 \pi_2^*}{\partial z^2} A + (1 - F(\pi_2^*)) \frac{\partial^2 \pi_2^*}{\partial z A} \) as the “direct effect” of \( z \) on \( A \). It is positive if increasing \( z \) raises the marginal monopoly or duopoly profit from the investment more than it increases the marginal cost of the investment. Second, we refer to \( \frac{\partial \pi_2^*}{\partial A} - \frac{\partial \pi_2^*}{\partial A} \) as the “competition effect” of \( z \) on \( A \). Given that \( z \) is normalized so that larger values of \( z \) are good for firm 2, a larger value of \( z \) makes it more likely that firm 2 will enter. Hence, a larger \( z \) makes firm 1 want to invest more when the competition effect is positive and less when it is negative.

The following simple proposition identifies a set of circumstances in which investment levels will be monotone in \( z \).

**Proposition 1** Let \( A^*(z) \) be the equilibrium investment level in the model of investment absent entry deterrence motivations described above. Suppose \( \frac{\partial \pi_2^*}{\partial z} > 0 \). Then \( A^*(z) \) is monotone nondecreasing if the direct and competition effects are nonnegative, and \( A^*(z) \) is monotone nonincreasing if the direct and competition effects are nonpositive.

\[ \text{Note that this does involve an additional assumption. We had earlier assumed just that } z \text{ was ordered so that } \frac{\partial \pi_2^*}{\partial z} > 0. \text{Because } \frac{\partial \pi_2^*}{\partial z} = \frac{\partial \pi_2^*}{\partial z} + \frac{\partial \pi_2^*}{\partial z} \partial z, \text{ the added assumption can be thought of as a requirement that the direct effect of } z \text{ on firm 2's profits is greater than the indirect effect that comes from firm 1 changing its investment level in response to changing market conditions. While this assumption is often satisfied, it is stronger than is necessary. By} \]
Proof

The first order condition for \( A^*(z) \) is

\[
\frac{\partial c}{\partial A}(A^*(z), z) = F(\pi_2^{d*}(A^*(z), z)) \frac{\partial \pi_2^{d*}}{\partial A}(A^*(z), z) + (1 - F(\pi_2^{d*}(A^*(z), z))) \frac{\partial \pi_1^{m*}}{\partial A}(A^*(z), z).
\]

Differentiating with respect to \( z \) gives

\[
\frac{\partial^2 c}{\partial A^2} \frac{dA^*}{dz} + \frac{\partial^2 c}{\partial z \partial A} = F(\pi_2^*) \left( \frac{\partial^2 \pi_1^{d*}}{\partial z \partial A} + \frac{\partial^2 \pi_1^{d*}}{\partial A^2} \frac{dA^*}{dz} \right) + (1 - F(\pi_2^*)) \left( \frac{\partial^2 \pi_1^{m*}}{\partial z \partial A} + \frac{\partial^2 \pi_1^{m*}}{\partial A^2} \frac{dA^*}{dz} \right)
\]

\[
+ f(\pi_2^{d*}(A^*(z), z)) \frac{d\pi_2^{d*}}{dz} \left( \frac{\partial \pi_1^{d*}}{\partial A} - \frac{\partial \pi_1^{m*}}{\partial A} \right),
\]

where we have written \( \frac{d\pi_2^{d*}}{dz} \) for the total derivative of \( \pi_2^{d*}(A^*(z), z) \) with respect to \( z \), \( \pi_2^* \) for \( \pi_2^{d*}(A^*(z), z) \), and where all derivatives are evaluated at \( (A^*(z), z) \).

Solving for \( \frac{dA^*}{dz} \) gives

\[
\frac{dA^*}{dz} = \frac{F(\pi_2^*) \frac{\partial^2 \pi_1^{d*}}{\partial z \partial A} + (1 - F(\pi_2^*)) \frac{\partial^2 \pi_1^{m*}}{\partial z \partial A} - \frac{\partial^2 c}{\partial z \partial A} + f(\pi_2^*) \frac{d\pi_2^{d*}}{dz} \left( \frac{\partial \pi_1^{d*}}{\partial A} - \frac{\partial \pi_1^{m*}}{\partial A} \right)}{\frac{\partial^2 c}{\partial A^2} - F(\pi_2^*) \frac{\partial^2 \pi_1^{d*}}{\partial A^2} - (1 - F(\pi_2^*)) \frac{\partial^2 \pi_1^{m*}}{\partial A^2}},
\]

where again all derivatives are evaluated at \( (A^*(z), z) \).

The denominator of this expression is always positive. Given the assumption that \( \frac{d\pi_2^{d*}}{dz} > 0 \), the numerator is a sum of the direct effect and the product of the competition effect and something that is nonnegative. Hence, \( A^*(z) \) will be monotone increasing if the two effects are positive and monotone decreasing if they are both negative.

QED.

One case for which the comparative statics are particularly simple is when \( z \) is just the number of potential consumers in the market and the profit and cost functions are directly proportional to \( z \).

expanding \( \frac{d\pi_2^{d*}}{dz} \) before solving for \( \frac{dA^*}{dz} \) it is easy to see that it suffices to instead add the assumption that

\[
\frac{\partial^2 c}{\partial A^2} - F(\pi_2^*) \frac{\partial^2 \pi_1^{d*}}{\partial A^2} - (1 - F(\pi_2^*)) \frac{\partial^2 \pi_1^{m*}}{\partial A^2} > f(\pi_2^*) \frac{d\pi_2^{d*}}{dz} \left( \frac{\partial \pi_1^{d*}}{\partial A} - \frac{\partial \pi_1^{m*}}{\partial A} \right).
\]

This will always hold if the direction in which firm 1 changes \( A \) as competition becomes more likely reduces firm 2’s profits (so that the right hand side is negative). For example, this would be the case for an investment in a form of norivalrous advertising which raised consumer awareness of or valuation for all products in a product class. Otherwise, it will be necessary the term on the right hand side not be too large, which will hold, for example, if the distribution of entry costs is sufficiently diffuse so that the density term is sufficiently small.
Corollary 1 In the model above, suppose $c(A, z) = zc(A, 1)$ and $\pi_i^{d*}(A, z) = z\pi_i^{d*}(A, 1)$ for $i = 1, 2$ and $j = d, m$. Then, the direct effect is zero. Hence $A^*(z)$ will be monotone increasing if the competition effect is always positive and $A^*(z)$ will be monotone decreasing if the competition effect is always negative.

2.2.2 Examples

In a number of simple models it is easy to see that investments are monotone in a parameter which indexes the attractiveness of the market to potential entrants.

Example 1 Advertising with spillover benefits to entrants.

Suppose that $z$ is the number of potential consumers in a market. Let $A$ be the per consumer advertising expenditure by the incumbent on a form of advertising which raises potential consumers’ valuations for all products in the product class. Suppose also that the advertising technology is such that the influence on each consumer (or the probability of reaching each consumer) is directly proportional to the per consumer expenditure. Then, $A^*(z)$ will be monotone decreasing.

In the pharmaceutical application, the proportional advertising costs assumption in the above example might be motivated by the idea that the number of patients reached will be proportional to detailing expenditures if patients are treated by specialists and the number of specialists is proportional to the number of patients with the condition in question. To see that such a technology leads to advertising expenditures which are decreasing in the size of the market, note first that, as we commented above, with profits and cost being assumed to be proportional to the size of the market there is no direct effect. In most models of nonfirm-specific advertising, the competition effect will be negative as firm 1 gets a smaller share of the customers when it has competition and the marginal benefit to raising consumers’ valuations may also be lower if prices in the duopoly equilibrium do not increase one for one with consumers’ increased valuations for products in the product class. Hence, we would expect per consumer advertising expenditures to be monotone decreasing.

Example 2 Differentiating advertising.
Again suppose that $z$ is the number of potential consumers and that $A$ is the per consumer advertising expenditure with the same technology as above. Suppose now, however, that the effect of advertising is to differentiate the products by intensifying consumers’ idiosyncratic tastes (or distastes) for firm 2’s product. Then, $A^*(z)$ will be monotone increasing.

Here again we have assumed that there is no direct effect. The competition effect will now be positive, because advertising will have no effect on monopoly profits but will increase duopoly profits by raising the equilibrium price. Hence, per consumer advertising expenditures will be monotone increasing.

We would also get the same result with another reasonable advertising technology. Suppose that $A$ represents total advertising expenditure in a model where the advertising technology (perhaps like direct-to-consumer television advertising) is such that all potential consumers see any ad, i.e., where $c(A, z) = c(A, 1)$ and $\pi_i^*(A, z) = z\pi_i^*(A, 1)$. In this case the direct effect of $z$ on $A$ is positive so the direct and competition effects work in the same direction.

**Example 3** Product proliferation.

Again suppose that $z$ is the number of potential consumers. Let $A$ be an expenditure on developing new versions of the product to be located at various points of a horizontal space of tastes. Suppose that costs of these development expenditures are independent of $z$, i.e., $c(A, z) = c(A, 1)$. Suppose also that second stage monopoly profits are only slightly increasing in $A$ because idiosyncratic taste variation is small relative to the value of the good, while duopoly profits are more steeply increasing in $A$ because product proliferation leads firm 2 upon entry to choose to compete directly with only a subset of firm 1’s products. Then, $A^*(z)$ will be monotone increasing.

In the pharmaceutical industry, a model like that sketched in the example might be applied to firms’ decisions as to how many presentations of a drug to develop, e.g., whether to market gelcaps, an oral solution, and 50 and 100mg tablets instead of just 50mg tablets. In such a model, the direct effect will be positive. Increasing the market size raises the benefit to the development expenditure without increasing its cost. The competition effect is also positive as we have described it. Hence, proliferation will be monotone increasing in the market size.
2.3 Nonmonotonicities with entry deterrence motivations

Suppose now that the incumbent’s investment choice is observed by firm 2 prior to firm 2 making its entry decision. Firm 1 may then have a strong incentive to distort its investment in the direction of reducing firm 2’s profit in order to reduce the probability that entry will occur. We discuss here how this may lead to a nonmonotonic relationship between investment levels and the attractiveness of the market to entrants.

When investment can serve to deter entry the first-order condition for firm 1’s investment choice is

\[
\frac{\partial c}{\partial A}(A^*(z), z) = F(\pi_2^d(A^*(z), z)) \frac{\partial \pi_1^d}{\partial A}(A^*(z), z) + (1 - F(\pi_2^d(A^*(z), z))) \frac{\partial \pi_1^m}{\partial A}(A^*(z), z) \\
+ (\pi_1^d(A^*(z), z) - \pi_1^m(A^*(z), z)) \frac{\partial \pi_2^d}{\partial A}(A^*(z), z) f(\pi_2^d(A^*(z), z)).
\]

This differs from the first-order condition of the previous subsection in the presence of the final term which reflects the incentive to deter entry. Looking at this term, it is apparent that the strategic entry deterrence motive will typically be nonmonotone. A multiplicative component is the density of the set of firm 2’s that in equilibrium are just indifferent between entering and not entering, \( f(\pi_2^d(A^*(z), z)) \). When a market is either extremely small so that entry is blockaded, or extremely attractive so that firm 2 will almost surely enter given any conceivable action by firm 1, this density is extremely small and the effect becomes negligible.\(^6\) In markets of intermediate size, however, the term is often quite large because another multiplicative component is the difference between monopoly and duopoly profits, and this is often much larger than the effect on profits of a small distortion in investment levels.

Adding the strategic entry deterrence motive to firm 1’s other incentives can easily lead to nonmonotone behavior. We present two examples below to illustrate some of the ways in which this may happen.

2.3.1 An example where advertising provides spillover benefits

Consider a version of the nonnirvalrous advertising model described in example 1 where a mass \( z \) of consumers have a type \( \theta \) which is uniformly distributed on \([0, 1]\). Suppose that after the

\(^6\)The effect being negligible at the extremes is, of course, something that need not be true in all models. For example, if the entry cost distribution is uniform on \([0, \bar{E}]\) then the density of the set of firm 2’s that are indifferent to entering is positive even in the smallest markets.
monopolist spends \( zA^2/2 \) on advertising, a consumer of type \( \theta \) receives utility \( \theta A - p_1 \) if he buys the (branded) good from firm 1 at price \( p_1 \), \( \frac{1}{2}\theta A - p_2 \) if he buys the (generic) good from firm 2 at price \( p_2 \), and zero if he buys neither good.

In this model it is easy to check that a monopolist in the final stage sets \( p_1 = \frac{4}{7} \) and receives profit \( \frac{2A}{7} \). If the firms compete as duopolists the equilibrium prices are \( p_1^* = \frac{2}{7}A \) and \( \frac{1}{17}A \) and the second stage profits are \( \frac{8}{49}zA \) and \( \frac{3}{49}zA \), respectively. The first order condition when advertising is not observed until after firm 2 enters is

\[
A_{na}^*(z) = \frac{1}{4} \left( 1 - F\left( \frac{zA_{na}(z)}{49} \right) \right) + \frac{8}{49} F\left( \frac{zA_{na}(z)}{49} \right) .
\]

When advertising can affect entry, the first order condition is

\[
A_{na}^*(z) = \frac{1}{4} \left( 1 - F\left( \frac{zA_{na}(z)}{49} \right) \right) + \frac{8}{49} F\left( \frac{zA_{na}(z)}{49} \right) - \left( \frac{1}{4} - \frac{8}{49} \right) \frac{zA_{na}(z)}{49} - f\left( \frac{zA_{na}(z)}{49} \right) .
\]

Figure 1 contains a graph of the equilibrium advertising levels in this model when the distribution \( F \) of entry costs is log normal with mean 0.0025 and variance 0.0015. In the model without entry deterrence motives, advertising levels decline smoothly from \( \frac{4}{7} \) at \( z = 0 \) to \( \frac{8}{49} \) in the limit as \( z \to \infty \).\(^7\) When there is also an entry deterrence motive, advertising levels are similar when \( z \) is small, but decrease more rapidly in markets of small to intermediate size as firm 1 increasingly distorts its advertising downward to deter entry. In larger markets, however, firm 1 begins to give up on entry deterrence, and this may cause the advertising levels to turn up for a while as they approach the equilibrium values of the model without entry deterrence.

### 2.3.2 An example where advertising differentiates products

Consider a specification of a model of differentiating advertising like that sketched in Example 2. Suppose that there is a mass \( z \) of potential consumers with unit demands differentiated by a taste parameter \( \theta \), which is uniformly distributed on \([-1, 1]\). Suppose that after firm 1 spends \( zA^2/2 \) on advertising, a consumer of type \( \theta \) receives utility \( 1 - p_1 \) if he buys the good from firm 1 at price \( p_1 \), \( 1 + \theta t(1 + A) - p_2 \) if he buys from firm 2 at \( p_2 \), and zero if he makes no purchase. In a slight \textit{ad hoc} departure from what was described earlier, suppose also that firm 1 receives an

\(^7\)Note that in order to show what happens as \( z \) goes from zero to infinity we have rescaled the x-axis on the graph using \( x = z/(z + 1) \).
additional direct benefit (general reputation?) equivalent to a profit of \( zA^2/2 \) from the advertising expenditure.\(^8\)

In this model a monopolist sets \( p_1 = 1 \) and receives profit \( zA^2/2 + z - zA^2/2 \). If firm 2 enters, the model is a standard one of differentiation on a line segment and we find \( p_1^* = p_2^* = t(1 + A) \). Firm 1’s profits are thus \( zA^2/2 + zt(1 + A)/2 - zA^2/2 \), and firm 2’s profits are \( z(1 + A)/4 \).

Suppose first that firm 1’s investment choice is not observed until after firm 2’s entry choice, so there is not entry deterrence motivation then. The first order condition for firm 1’s investment level, \( A_{nA}(z) \), is then

\[
A_{nA}(z) = \frac{1}{2} + \frac{t}{2} F(zt(1 + A_{nA}(z))/2).
\]

When investments can help to deter entry the first order condition is

\[
A_{dA}(z) = \frac{1}{2} + \frac{t}{2} F(zt(1 + A_{dA}(z))/2) - \frac{z}{2} \left(1 - \frac{t(1 + A)}{2}\right) f(zt(1 + A_{dA}(z))/2).
\]

Figure 2 contains a graph of the equilibrium advertising levels, \( A_{dA}(z) \) and \( A_{nA}(z) \), when the \( t = 0.25 \) and the distribution \( F \) of entry costs is lognormal with mean 0.25 and standard deviation 0.25. The advertising levels in the model without strategic entry deterrence increase smoothly and gradually from \( \frac{1}{2} \) to \( \frac{5}{8} \). In constrast, in the model with entry deterrence the advertising levels are similar at the extremes but show a sharp dropoff at intermediate values of \( z \). A pattern like this is typical of models where the entry deterrence motive is in conflict with the direct/competition effects and where the range of the market size variable is large compared to the range of the entry cost distribution.

Other similar patterns are also possible. In the model above, \( z \) had no direct effect on \( A \). If the model had a moderately strong direct effect we would have seen an up-down-up pattern to advertising levels, with \( A_{dA}(z) \) increasing along with \( A_{nA}(z) \) at both ends and only turning down in the middle.

\(^8\)We make this change because in this model, firms reduce advertising to deter entry. Without the \textit{ad hoc} modification, however, this effect will not be apparent because in the \( z = 0 \) limit, there is no benefit to advertising and the optimal level is already zero.
3 Data

Our basic data set includes sixty three drugs that faced potential generic entry as the result of a patent or FDA exclusivity expiration between 1986 and 1992.\(^9\)

We collected the data on revenues, prices, and advertising from historical IMS audits of the pharmaceutical industry. Like all IMS sales data, the prices and revenues are those paid by the retail or hospital sector, in other words, essentially at the wholesale level. The primary revenue data that we use is the revenue from hospital and drugstore sales separately in each of the three calendar years prior to, in the year of, and in the year following each drug’s patent expiration. We construct two variables from this data which we use to help measure the attractiveness of the market to potential entrants: Revenue\(_3\) is the average annual revenue from hospital and drugstore sales in the three calendar years before but not including the year of patent expiration; and HospFrac is the fraction of total revenues in the calendar year prior to patent expiration which were due to hospital sales. All prices and revenues are in constant 1982-1984 dollars.

A single manufacturer typically sells a given prescription drug in a number of presentations. Our revenue data contain annual presentation-level wholesale revenues for all presentations of each drug in both the hospital and drugstore submarkets for five years: three years prior to patent expiration, the year of patent expiration and the year following patent expiration.\(^10\) The primary variable we use to measure the degree to which an incumbent has chosen to proliferate presentations, PresHerf, is a variant on a Herfindahl index of the presentation-by-presentation revenues. Specifically, if \(w_i\) is the fraction of the sales of drug \(i\) which are made through drugstores and \(z_{ita}\) and \(z_{ihkt}\) are the fractions of drug \(i\)’s revenues in year \(t\) in the drugstore and hospital markets, respectively, which are accounted for by presentation \(k\), we set \(\text{AvgHerf}_{ia} = w_i \sum_k z_{ita}^2 + (1 - w_i) \sum_k z_{ihkt}^2\).\(^11\) PresHerf will be large in markets where a small number

\(^9\)These drugs are a subset of those used in set of Scott Morton (1995). Our preliminary data on patent expiration dates were obtained from Fiona Scott Morton and the advertising data were collected jointly with her for use in this paper and in Scott Morton (1995).

\(^10\)Defining presentations by differences at the wholesale level will in some cases be a poor reflection of how proliferation affects the costs of entry into a product segment. For example, 100mg tablets sold to pharmacies in a 100 tablet bottle will be treated as different from 100mg tablets sold in bubble packs and as different from 100mg tablets sold to pharmacies in a 500 tablet bottle. The descriptors in our data at times do not make it clear how similar/different wholesale presentations are, but it did not appear that problems like those described above are very important in the aggregate.

\(^11\)We would regard it as preferable to sum the presentation by presentation revenues across the two markets and then compute a sum of squared market shares, but given the form of our data, this would have entailed a laborious manual
of presentations account for most of the revenues and smaller in markets where sales are more evenly divided among a larger number of presentations.

Because of the different presentations, a drug’s price is difficult to define. (Prices for different presentations are clearly not set to equalize the total cost of a duration of treatment or in proportion to the quantity of the active ingredient.) In our study of pricing patterns, we look at changes in the drugstore and hospital prices of each drug using variables, \( HPrice \) and \( DPrice \), which give the price of one particular presentation of each drug in the five year window around the year of patent expiration.\(^{12}\)

Our advertising data on each drug consist of two variables, \( Detail \) and \( Journal \), giving minutes spent on pharmaceutical company “detailers” promoting the drug in direct conversations with physicians, and estimates of dollars spent on journal advertisements promoting the drug, based on audits of medical journals, respectively. Detail advertising is generally the much more important form of advertising for drugs (at least in terms of total expenditure). The advertising data is at a monthly frequency and includes 48 observations per drug covering the thirty six months prior to patent expiration, the month of patent expiration and the eleven subsequent months.

Three additional variables were collected from \textit{Drug Facts and Comparisons},\(^{13}\) \textit{Physician’s Desk Reference}, the FDA’s \textit{Approved Drug Products with Therapeutic Equivalence Evaluations}, and discussions with physicians. \( TherSubs \) is the number of other molecules in a drug’s therapeutic class, where we used therapeutic categories defined by \textit{Drug Facts and Comparisons}. \( Chronic \) is set to zero for drugs which treat an acute condition and to one for drugs which treat a chronic condition.\(^{13}\) \( Entry3Yr \) is a dummy variable equal to one if at least one firm had an Abbreviated New Drug Application (ANDA) approved (allowing it to produce a generic version of the drug) within three years of the date at which a patent expires.\(^{14}\)

Summary statistics for these variables are presented in Table 2.

One difficult aspect of the creation of the dataset is that patent expirations in pharmaceuticals are not always straightforward or easy to verify. Innovating drug manufacturers are required by the

\(^{12}\)We usually chose the presentation that had the highest revenue in the first year of our data.

\(^{13}\)The variable is set to one-half for a few drugs which were judged to be intermediate on this dimension.

\(^{14}\)Caves, Whinston and Hurwicz (1991) and Scott Morton (1995) note that entry in pharmaceutical markets often does not occur immediately upon patent expiration, and that only part of the delay in attributable to uncertainties in the length of time necessary for ANDA approval.
FDA to report all relevant patents and the expiration dates of those patents. The FDA publishes this information in the Approved Product List (“The Orange Book”). The FDA, however, has no way to check the validity of the information given to them by the manufacturers. In fact, years of litigation is sometimes necessary to resolve the issue of which patents are relevant. It is clearly in the interests of the manufacturers to list more rather than fewer patents if there is a question as to which patent or patents might be binding. We, therefore, checked various sources to verify each of the patent or exclusivity expirations. For the high revenue drugs, potential entry dates are often listed in trade publications and are, therefore, fairly easy to track down, absent court battles over expiration. Information is more difficult to come by for the smaller revenue drugs because potential entry into those drugs is usually not an important event. For those we relied more on FDA publications. Additional sources we used were lists of patent expiration dates published by the Generic Pharmaceutical Industry Association and Arthur D. Little, Caves, Whinston, and Hurwitz (1991), lists of ANDAs, and information on generics being produced in various issues of Drug Facts and Comparisons. A number of drugs from our original list were dropped because we did not feel that we could reliably determine patent expiration dates.

4 Predicting entry

Our primary empirical goal in this paper is to examine the behavior of pharmaceutical incumbents in the period immediately prior to patent expiration. In particular, we will be concerned with how behavior varies with our perception of the attractiveness of the market to potential entrants. In this section we carry out a prerequisite to this analysis—an estimation of what characteristics of markets make them attractive to potential entrants.

We estimate a probit model where the dependent variable is our dummy variable for whether generic entry occurred. Our right hand side variables are the log of the drug’s revenues in the three years prior to patent expiration, the fraction of the drug’s sales made to hospitals, our chronic/acute variable, and the log of the number of drugs in the therapeutic class, i.e., we estimate

\[
Entry_{Yr_i}^* = \beta_0 + \beta_1 \log(Revenue_{i}) + \beta_2 HospFrac_i + \beta_3 Chronic_i \\
+ \beta_4 \log(TherSubs_i) + \epsilon_i
\]
\[ Entry3Yr = \begin{cases} 
1 & \text{if } Entry3Yr^* > 0 \\
0 & \text{otherwise.} 
\end{cases} \]

The results of estimating this equation on our sixty four drug sample are shown in Table 3. Even with our limited sample we obtain highly significant evidence that drugs with higher revenues are most likely to attract generic entry. The point estimates are that drugs treating chronic conditions and drugs sold through hospitals were more likely to face generic entry, although neither estimate is significant even at the 10% level. We would also find such estimates a bit surprising as they do not conform with intuitive findings in the previous literature about where markups are greatest: Sorensen’s (1998) study of dispersion in retail drug prices in New York State indicates that drugs treating acute conditions have higher retail markups (and less dispersion) and Ellison (1998) and others report that hospitals pay lower wholesale prices for antibiotics than do drugstores.\textsuperscript{15}

The most important aspect of the model for our purposes is whether the predictions are sharp enough to allow us to classify some drugs as very unlikely to face generic entry, some as almost sure to face generic entry, and some as intermediate cases. In subsequent sections we will often refer to drugs as having a low, medium, or high entry probability depending on whether the predicted entry probability from our probit model is less that 0.3, between 0.3 and 0.8, or at least 0.8. This scheme classifies 18 drugs as having a low entry probability, 20 as having a medium entry probability and 25 as having a high entry probability. We denote the predicted entry probability from this model by \( EntryProb \). We write \( LowEntryProb \), \( MidEntryProb \), and \( HiEntryProb \) for the dummy variables which indicate whether the predicted entry probability falls into each of the three groups.

5 Incumbent behavior: advertising

In this section we examine the advertising expenditures of pharmaceutical incumbents in the period immediately prior to the expiration of their patent protection. We have expenditure data for two forms of advertising: detailing and journal advertising. We look for evidence of distortions due to entry deterrence by comparing advertising expenditures across drugs in two ways: normalizing

\textsuperscript{15}Scott Morton (1995) does report that entry is significantly more likely for drugs treating chronic conditions and for drugs where the hospital share of sales is larger in her analysis of a larger dataset which overlaps substantially with ours.
advertising expenditures by sales and looking at advertising levels immediately prior to patent expiration relative to earlier levels.

In general, we will think of the strategic entry deterrence motive as providing firms in “intermediate” markets with an incentive to reduce advertising intensity. Advertising for pharmaceuticals, of course, may serve a number of purposes. It may inform doctors of the existence of a product, provide them (perhaps selectively) with information on the safety and efficacy of a product for various uses, or simply help them to remember a drug’s name. Because doctors know that generic and branded drugs are chemically equivalent and many states have laws mandating that pharmacies dispense a generic drug unless the doctor has specifically forbidden it, any of these benefits of advertising will also accrue in part to generic entrants. As a result, the prediction of a standard strategic investment model would be that pharmaceutical firms interested in deterring generic entry would distort advertising levels downward. Alternatively, if one thinks of an informational linkage where advertising affects future entry by signaling profitability, one would again conclude that firms will reduce advertising to deter entry. One can, of course, think of models where this is not true, e.g., advertising that voices concerns about the quality of generics.

Our empirical goal in this section will be to examine advertising intensity around the time of patent expiration for a sample of drugs. Besides describing the general patterns, it will be interesting to note any evidence of nonmonotonicity in the advertising intensities. A finding that is consistent with entry deterring behavior is that in the years prior to patent expiration, firms seem to reduce both detail and journal advertising expenditure most rapidly in markets of intermediate size.

5.1 Detail advertising

Our first advertising variable is the quantity of “detailing” time by pharmaceutical company representatives. Fifty one of the sixty nine\(^{16}\) branded drugs for which we have data engage in detail advertising at some point in the three years prior to patent expiration.\(^{17}\) The mean across

\(^{16}\)The sample contains seventy branded drugs rather than sixty three because a few of the drug molecules included as single observations in our entry regressions were produced under separate brand names by two manufacturers under joint marketing agreements. When we have separate advertising data for the separate brand names, we treat the brand names as separate observations in the regressions and use brand-specific revenues when forming advertising to sales ratios.

\(^{17}\)Drugs with very low revenues typically do not engage in detail advertising. Thirteen of the eighteen drugs which are not observed to engage in detail advertising are in our low predicted entry probability group.
drugs of the ratio of total detailing (in 1000’s of minutes) in the three years prior to expiration to total revenues in that period (in 1000’s of dollars) is 0.0048 and the standard deviation is 0.0075. At $10 a minute for detailing, that would imply an advertising to sales ratio of around 5%, consistent with industry norms.

As we mentioned earlier, an assumption that detail advertising costs are proportional to the number of potential consumers reached might be reasonable if patients are treated by specialists so that the number of potential patients reached by a marketing representative in one visit to a doctor could be roughly independent of the prevalence of the condition the drug treats. With this assumption there is no direct effect of market size on per consumer advertising and it seems plausible that entry deterrence motivations might be strong enough to create a nonmonotonicity in the advertising-to-sales ratio. Across drugs detail advertising does appear to be roughly proportional to revenues: if one regresses \( \log(1 + \text{Detail3}) \) on a constant and \( \log(\text{Revenue3}) \) one gets a coefficient of 0.91 on the log revenue with a t-statistic of 7.89.

For a first look at how the detailing-to-sales ratio varies with the predicted probability of generic entry, we estimate the regression

\[
\frac{\text{Detail3}_i}{\text{Revenue3}_i} = \beta_0 + \beta_1 \text{EntryProb}_i + \beta_2 e^{-(\text{EntryProb}_i - \frac{1}{2})^2/0.2^2} + \epsilon_i,
\]

where \( \text{Detail3}_i \) is the average annual detailing expenditure for drug \( i \) in the thirty six months prior to patent expiration, \( \text{Revenue3}_i \) is drug \( i \)'s average annual revenue in the three calendar years prior to patent expiration and \( \text{EntryProb}_i \) is the predicted probability of entry from the model of Section 4. The inclusion of the nonlinear function of \( \text{EntryProb}_i \) is motivated by a desire to see whether advertising levels are unusually low for drugs facing an intermediate probability of entry. (The function \( \exp(-(x - \frac{1}{2})^2/0.2^2) \) achieves a maximum of one when \( x = \frac{1}{2} \) and declines smoothly to about 0.1 by the time \( x \) is 0.2 or 0.8.) When \( \beta_2 \) is sufficiently large in absolute value (specifically when \( |\beta_2| > |\beta_1|/4.288 \)) this function will be nonmonotonic.

The results from this regression are presented in the first column of Table 4. While the point estimate on the nonlinear function of the predicted entry probability indicates that detail advertising is lower for drugs facing an intermediate probability of generic entry, we find no significant evidence of nonmonotonicity and the \( R^2 \) of the regression is low. Table 5 further illustrates that the lack of a strong relationship between the detail advertising-to-sales ratio and our
predicted entry probabilities. Dividing the drugs into the groups of those with “low”, “medium”, and “high” predicted entry probabilities, we find that the values of $Detail3/Revenue3$ in the three groups are 0.0040, 0.0042, and 0.0057, respectively. The within group standard deviations are 0.011, 0.006, and 0.006.

As another way to get at the question of whether detailing expenditures are unusually low in markets of intermediate size we look also at trends in advertising, estimating the equations

$$\frac{Detail_{it}}{Detail_{3i}/12} - 1 = (\beta_1 LowEntryProb_i + \beta_2 MidEntryProb_i + \beta_3 HiEntryProb_i)Time_t + \epsilon_{it},$$

and

$$\frac{Detail_{it}}{Detail_{3i}/12} - 1 = (\beta_1 + \beta_2 EntryProb_i + \beta_3 e^{-(EntryProb_i-0.5)^2/0.22})Time_t + \epsilon_{it},$$

where $i$ indexes drugs, $t$ indexes the 36 months prior to patent expiration, $LowEntryProb$, $MidEntryProb$, and $HiEntryProb$ are dummies for whether $EntryProb$ lies in $[0,0.3]$, $(0.3,0.8]$, or $(0.8,1]$ and $Time_t$ is time. We normalize $Time_t$ so that it takes on a value of -1 thirty six months prior to patent expiration and a value of 1 in the month immediately prior to expiration.

The specifications are an attempt to take advantage of the known patent expiration dates. Advertising levels at the start of our data may primarily reflect the costs and benefits of advertising to a monopolist. As the date of patent expiration approaches advertising levels may change for three reasons: levels may naturally change as the product ages, firms begin to take into account that some of the advertising stock they are building may affect duopoly rather than monopoly profits (i.e. advertising changes in the direction of the competition effect), and the entry deterrence motive becomes relevant. Again, the entry deterrence motive will be strongest in markets of intermediate size. If the entry deterrence motive is strong enough to outweigh the competition and life-cycle effects, we may see a nonmonotonic pattern in advertising trends with advertising decreasing most rapidly in markets of intermediate attractiveness.

The results of estimating the first equation are presented in column 1 of Table 6.\textsuperscript{18} We obtain significant evidence that detail advertising is decreasing for drugs in the medium entry probability

\textsuperscript{18}The sample consists of thirty six monthly observations on the fifty one drugs for which detail advertising is not always zero. The equation is estimated by OLS with robust standard errors computed allowing for serial correlation of the errors for observations from the same drug.
group, and insignificant estimates indicating that detailing is changing more slowly in the other two groups. In pairwise tests, the estimated slope coefficient for the medium entry drugs is different from the coefficient for the low group at the 10 percent level and is different from the coefficient for the high group at the 1 percent level.

Estimates of the second equation, where the rate of change in advertising is a continuous function of the entry probability, are presented in column 2 of Table 6. The estimated coefficient on the linear term is positive. The coefficient on the nonlinear term is negative and significant at the 1 percent level, again reflecting that advertising decreased more rapidly over the preexpiration period for drugs facing an intermediate probability of entry. The fitted slopes from the regression are nonmonotone in the entry probability, and we can reject at the 1% level that $\beta_2$ and $\beta_3$ are equal to any combination that would make the slope a monotone function of $EntryProb$.

One might worry that a test based on examining ratios of monthly advertising levels to total advertising for a drug could be heavily influenced by the uneven advertising of drugs with very low total advertising. To provide a more robust verification of the pattern noted above, we report in the first row of Table 7 the number of drugs in each of the three groups for which detail advertising was at least as high on average in the year prior to patent expiration than in the two years before that. We find that only two of the twenty drugs with a medium entry probability show an increase in detailing, while such a pattern is found for three of six drugs with a low entry probability and sixteen of twenty five drugs with a high entry probability.

To provide a formal test of the hypothesis that the probability that detail advertising is increased in the year prior to expiration is nonmonotone in the predicted entry probability, we use a generalized likelihood ratio test with the null that the frequencies in Table 7 are realizations from three binomial distributions with weakly monotonic probabilities. Since the probability of type I error for such a test will, in general, depend on the null binomial probabilities from the three groups, we employed a conservative testing procedure whereby we chose as our critical value the lowest 5% critical value resulting from a grid search of null binomial probabilities. Even so, we are able to reject monotonicity.

To provide a further look at the patterns of detail advertising prior to patent expiration and to also give a quick glance at what happens after patent expiration, Figure 3 presents kernel regression estimates of the relationship between normalized detail advertising, $12Detail_{it}/Detail_{3i}$, and time.
for three subsamples of drugs with “low”, “medium”, and “high” predicted entry probabilities. The figure graphs the ratio of the fitted value in month $t$ to the fitted value in month -36.\(^{19}\)

In the figure, detail advertising seems to have a steady downward trend in the preexpiration period for drugs in the medium entry probability group, while each of the other groups appears to have an upward bulge in advertising nine to eighteen months prior to patent expiration. The bulge suggests that part of the contrast between the detailing trends of medium and high entry probability drugs may be due to firms in the high group launching advertising campaigns to prepare for generic entry. We find it notable that almost none of the drugs in the medium-entry probability group undertake such a campaign.

While detail advertising levels are fairly flat around the time of patent expiration for drugs in the medium entry probability group, there is a pronounced drop off around this time in the low and high entry probability groups. With our normalization (roughly dividing advertising levels by the observed level right at the start of our dataset) the pattern is that detail advertising in the low and high groups rises well above the level in the medium group, and then drops off sharply to approach, at the end of the sample, the same total dropoff that is observed in the medium entry probability group.

5.2 Journal advertising

Our second advertising variable is the monthly expenditure for each drug on advertisements in medical journals. Journal advertising is generally thought of as less important than detail advertising. In our sample the mean of the ratio of total expenditure in the three years prior to patent expiration to a drug’s total revenues in that period is 0.013, or about one-fourth to one-third of what the firms may be spending on detail advertising. Again, not all drugs advertise in journals; only forty eight of the branded drugs in our sample are observed to advertise in journals in the three years prior to patent expiration. Because many medical journals reach a fairly wide audience of doctors one would expect that the cost of journal advertising per potential customer reached may tend to decrease in the size of a drug’s market. In our data this is borne out in the journal advertising-to-sales ratios—in a regression of the $\log(1 + \text{Journal3})$ on $\log(\text{Revenue3})$ we find

\(^{19}\)The kernel regression estimates were obtained using an Epanechnikov kernel with a window width of 10 months. The set of drugs used is the complete set of fifty one drugs for which Detail3 is nonzero. There are six drugs in the low entry probability group, twenty in the medium group and twenty five in the high group.
a coefficient of 1.18 with a standard error of 0.12. Only three of the nineteen drugs in the low entry probability group are observed to do any journal advertising.

While the fact that the advertising to sales ratio increases relatively rapidly with market size seems likely to obscure any potential nonmonotonicity, we begin our analysis again by estimating a regression of an advertising-to-sales ratio on the predicted entry probability and the same nonlinear function of the predicted entry probability as before,

\[
\frac{\text{Journal}_{3, i}}{\text{Revenue}_{3, i}} = \beta_0 + \beta_1 \text{EntryProb}_i + \beta_2 \exp\left(-\left(\text{EntryProb}_i - \frac{1}{2}\right)^2/0.2^2\right) + \epsilon_i.
\]

The results are presented in the second column of Table 4. The coefficient on the linear term is positive and significant. The coefficient on the nonlinear term is not significant (although the point estimate is negative and sufficiently large so as to make the fitted values nonmonotone).

An analysis of journal advertising trends should not be affected by the presence of a direct market size effect and thus may be more likely to uncover nonmonotone patterns. We estimate the regressions

\[
\frac{\text{Journal}_{4, i}}{\text{Journal}_{3, i/12}} - 1 = (\beta_1 \text{LowEntryProb}_i + \beta_2 \text{MidEntryProb}_i + \beta_3 \text{HiEntryProb}_i) \text{Time}_t + \epsilon_{it},
\]

and

\[
\frac{\text{Journal}_{4, i}}{\text{Journal}_{3, i/12}} - 1 = (\beta_1 + \beta_2 \text{EntryProb}_i + \beta_3 \exp\left(-\left(\text{EntryProb}_i - \frac{1}{2}\right)^2/0.2^2\right)) \text{Time}_t + \epsilon_{it},
\]

on the thirty six monthly observations prior to patent expiration for the forty eight drugs for which journal advertising is not always zero. The results are presented in the third and fourth columns of Table 6. In the specification based on dividing the drugs into the three groups, we obtain an estimate (significant at the 5 percent level) indicating that the medium entry probability drugs are reducing journal advertising over time and an estimate indicating that journal advertising is changing very little among high entry probability drugs. The difference between the medium and high group coefficients is significant at the 10 percent level. Unfortunately, the fact that only three low drugs do any journal advertising makes it impossible to provide significant comparisons between the low group and the other groups.

The second row of Table 7 again tries to provide potentially more robust evidence of nonmonotonicity by counting the number of drugs for which journal advertising is on average higher.
in the year prior to the patent expiration than in the two years before that. We find that this is true for one of the three drugs in the low entry probability group, four of the seventeen drugs in the medium group and ten of the twenty seven drugs in the high group.

To provide a further look at the patterns of journal advertising prior to patent expiration and to also give a quick glance at what happens after patent expiration, Figure 4 presents kernel regression estimates of the relationship between normalized journal advertising, $12 \text{Journal}_{it}/\text{Journal}_{3t}$, and time for drugs with medium and high predicted entry probabilities. In the pre-expiration period, journal advertising seems to have a downward trend in the medium entry probability group, while it is fairly flat for the high entry probability drugs. After patent expiration, journal advertising turns down for the high entry probability group, and rises in the medium entry probability group. We are not sure what to make of this apparent rise. It is entirely attributable to presence in the medium entry probability sample of all three of drugs with the largest increases in advertising post-expiration: Flexeril (which increases journal advertising in the year after expiration by 717% relative to its level in the preexpiration years), Ddavp (300%), and Ornade (144%). We would not, however, want to dismiss the possibility that there is something important to be learned from the experience of these three drugs.

Overall, we regard the results of this section as providing at least some evidence of the reduction in journal advertising that might be predicted to occur in drugs facing an intermediate probability of entry in a strategic investment model. While we can not detect any patterns in the level of advertising using advertising to sales ratios, detail advertising does seem to be unusually low in the period just prior to patent expiration for branded drugs which face an intermediate probability when we compare advertising just before patent expiration to the advertising for the same drug in an earlier period. Where the data is not too sparse, the patterns of journal advertising appear to be fairly similar to those of detail advertising.

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20 The low group was omitted because of the small number of drugs with nonzero journal advertising. The kernel regression estimates were obtained using an Epanechnikov kernel with a window width of 10 months. The set of drugs used is the complete set drugs in the medium and high probability groups for which Detail3 is nonzero. There are eighteen in the medium group and twenty seven in the high group.
6 Incumbent behavior: proliferation of presentations

Pharmaceutical products are typically produced in a variety of “presentations.” Antibiotics, for example, are frequently sold in tablets with varying amounts of the active ingredient and in caplets, and sometimes also sold in suspensions for pediatric use and intravenous solutions. Injectable drugs may be sold both in vials and in disposable syringes. Topical medications are usually be sold in various strength creams and lotions. In this section, we examine the the practices of pharmaceutical incumbents along this dimension. One finding consistent with a strategic entry-deterrence story is that incumbents in markets with an intermediate entry probability appear to increase presentation proliferation just prior to patent expiration.

Substantial fixed costs are incurred in developing and marketing each presentation of a particular drug.\textsuperscript{21} As a result, one would expect that the number of presentations introduced will typically be larger for more popular drugs. When an incumbent sells more presentations of a drug, potential entrants will either have to spend more on development to compete with an incumbent’s full product line or leave part of the market uncontested. Hence, it seems reasonable to suppose that an incumbent might attempt to strategically deter entry by increasing the number of presentations of its product.

As mentioned earlier, the primary variable we use to measure the degree to which an incumbent has chosen to proliferate presentations, $PresHer_f$, is a variant on a Herfindahl index of the presentation-by-presentation revenues. A firm wanting to make entry less attractive might try to do so either by introducing a new presentation of its product or by convincing some consumers to switch from a more popular presentation to a less popular presentation. Changes of either type would be reflected as a reduction in the presentation Herfindahl.

The fact that pharmaceuticals are often produced in many presentations is well known. Economists who work with pharmaceutical data refer to the fact all the time in bragging or complaining about the level of detail in their data. The first observation we would like to make from our data is that while a typical product is sold in many presentations, most often a few presentations account for most of the revenues. We define $PresHer_f3_i$ to be the average of

\textsuperscript{21}The amount of fixed costs will vary substantially, depending on whether FDA approval is needed for a new presentation.
Pres\(Herf_{it}\) over the three years prior to patent expiration.\(^{22}\) In our seventy drug sample, the mean number of presentations sold is 6.48, but the mean of \(Pres\)\(Herf_{3}\) is only 0.54 and for only eight drugs is \(Pres\)\(Herf_{3}\) below 0.2.\(^{23}\)

Table 8 reports the means of \(Pres\)\(Herf_{3}\) in the subsamples of drugs with low, medium and high predicted entry probabilities.\(^{24}\) As expected, the data indicate that the presentation Herfindahl is substantially larger for drugs in the low group than for drugs in the medium or high groups. It is notable, however, that even in the high entry probability group the presentation Herfindahl is not very small. The fact that the average presentation Herfindahl in the medium group is close to that for the high group despite the direct effects leading firms to introduce more presentations of more popular drugs might be taken to suggest that presentation Herfindahl’s in the medium group are unusually low. There does not, however, appear to be evidence of a nonmonotonic relationship.

For another look at this question, we present in Table 9 estimates from the regression

\[
Pres\text{\()Herf_{3i}\ \} - \beta_0 + \beta_1 Entry\text{Prob}_i + \beta_2 e^{-(Entry\text{Prob}_i - \frac{1}{2})^2/0.2^2} + \epsilon_i.
\]

The negative coefficient on \(Entry\text{Prob}\) confirms that there is significantly more presentation proliferation in larger markets. We find no evidence of nonlinearity or nonmonotonicity.

As a second way to get at the question of whether there is more presentation proliferation for drugs which face an intermediate probability of generic entry, we again estimated a model based on trends, not levels. Specifically, we examined whether the presentation Herfindahl was low in the year just before patent expiration relative to the previous two years by estimating the regressions,

\[
\frac{Pres\text{\()Herf_{it}\}}{Pres\text{\()Herf_{3i}\}} - 1 = (\beta_1 Low\text{Entry\text{Prob}}_i + \beta_2 Mid\text{Entry\text{Prob}}_i + \beta_3 Hi\text{Entry\text{Prob}}_i) Time_{it} + \epsilon_{it},
\]

and

\[
\frac{Pres\text{\()Herf_{it}\}}{Pres\text{\()Herf_{3i}\}} - 1 = (\beta_1 + \beta_2 Entry\text{Prob}_i + \beta_3 e^{-(Entry\text{Prob}_i - \frac{1}{2})^2/0.2^2}) Time_{it} + \epsilon_{it},
\]

\(^{22}\)For seven of the drugs we are missing data for one of the three years. In these cases the average was taken over the two years for which data was available.

\(^{23}\)Recall that we do not have data on particular presentations matched across hospitals and drugstores. The 6.48 number is based on looking year-by-year at the maximum of the number of presentations sold in drugstores and the number sold in hospitals and thus may underestimate the total number of presentations. Recall also that our Herfindahls are based on packaging at the wholesale level—a very liberal definition of what constitutes a different presentation.

\(^{24}\)The three subsamples contain nineteen, twenty one, and thirty drugs, respectively.
using the three annual pre-expiration observations we have for each of the 70 drugs in our sample.\textsuperscript{25}

The results from these regressions indicate the presence of a nonmonotone relationship. Estimates from the first regression are presented in column 1 of Table 10. The significant coefficient estimate on the \( \text{MidEntryProb}_t \times \text{Time}_t \) interaction indicates that drugs which face an intermediate probability of entry are decreasing their presentation Herfindahl by about eight percent in the period prior to patent expiration. The point estimates are that the presentation Herfindahls are decreasing more slowly for the drugs in the other two groups, and neither of these estimates is statistically significant. In pairwise tests, the coefficient for the medium entry probability group is significantly different from the low group coefficient at the 10 percent level, but is different from the high group coefficient at only the 29 percent level. Results from the continuous specification are presented in column 2. The coefficient on the nonlinear term, which again indicates that drugs facing an intermediate probability of entry are proliferating presentations most rapidly, is significant at the ten percent level.

Table 11 presents counts of the number of drugs in each group for which the presentation Herfindahl is higher and lower in the year before patent expiration than it was on average in the previous two years. In the low and high entry probability groups it is at least as common to see the presentation Herfindahl increase as it is to see it decrease. In the medium group the presentation Herfindahl decreases in 14 cases and only increases in 6.\textsuperscript{26}

Figure 5 provides a further look at patterns of product proliferation both before and after patent expiration. The figure graphs the mean within each entry probability category in each year the presentation Herfindahl (rescaled so that the value in the third year prior to patent expiration is one for each drug.)\textsuperscript{27} Drugs in the mid-entry probability group appear to have the largest decrease in the presentation Herfindahl prior to patent expiration. There is also a tendency in all classes for the presentation Herfindahl to be reduced in the year of and the year following expiration, and this is most pronounced for drugs in the high-entry probability group.

\textsuperscript{25}Again, seven drugs had one observation missing, so the sample includes only 203 data points. The \( \text{Time} \) variable is scaled to take on a value of -1 in the third year prior to patent expiration, and a value of 1 in the year immediately prior to patent expiration.

\textsuperscript{26}There are ten drugs for which the presentation Herfindahl is unchanged: eight in the low group and one each in the medium and high groups. For each of these drugs only one presentation of the drug is sold throughout the period.

\textsuperscript{27}The presentation Herfindahl is missing in the third year prior to patent expiration for five drugs. The scaling factor for these drugs is chosen so that the scaled presentation Herfindahl in the first year for which data is available matches the average of the scaled presentation Herfindahls for the other drugs in that class in that year.
7 Incumbent behavior: pricing

In this section, we examine the pricing decisions of pharmaceutical incumbents around the time of patent expiration.

The theoretical literature has identified a number of ways in which pricing decisions may affect subsequent entry: prices may signal something about the incumbent or the market to the entrant, they may be be distorted for signal jamming reasons, or there may be some more direct link between periods due to switching costs, learning by doing, etc.28 In the pharmaceutical industry we would regard signaling or signal-jamming as the most plausible mechanisms by which prices could affect future entry and think of the future profitability of the market as the primary unknown which generics are trying to learn.

How might incumbents distort their prices to make generic firms think that a market is not worth entering? Our discussions with industry sources suggest that generic firms are relatively well-informed about prices and revenues (and have all the same data we have). Generic firms are less likely to be well informed about price elasticities. Hence, it might be plausible to imagine that firms could choose prices that are too low from the perspective of static profit maximization in order to convince generic entrants that it will be profitable for them to continue to charge low prices after generic entry. (Branded manufacturers rarely appear to engage in vigorous price competition with generic entrants.) Incumbents distorting their prices down in advance of entry might also provide an additional explanation for the observation that incumbents sometimes raise prices following generic entry.

One situation in which the opposite distortion in prices might be expected is when the incumbent also sells another product in the therapeutic category that has a greater remaining patent life. In such a situation, a strategy for dealing with generic entry which has been mentioned to us is to try to induce consumers of the product with the expiring patent to switch to the other product. One way to do this is to launch an advertising campaign for the newer product. Another may be to raise the price of the older product.

Comparing price levels across different drugs makes little sense (in the absence of good data on elasticities) so our analysis will focus entirely on patterns in price changes. Figure 6 presents

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28 Among the classic papers in this literature are Milgrom and Roberts (1982), Fudenberg and Tirole (1983b, 1986) and Klemperer (1987).
price indexes for drugs facing low, medium and high probabilities of entry in both the drugstore and hospital submarkets. The index for group $g$ at time $t$, $I_{gt}$, is computed by setting the index to one in the initial year of the data and then setting the ratio $I_{gt}/I_{gt-1}$ equal to the mean across drugs in group $g$ of the ratio of year $t$ to year $t - 1$ prices. All prices are first deflated using the Bureau of Labor Statistics’ producer price index for prescription pharmaceuticals, so our indexes reflect changes in prices relative to the aggregate trends in pharmaceutical prices. As noted above, the drugs in our sample are typically produced in a number of presentations, and the market shares of the various presentations change over time. We have chosen to measure the price changes for each drug simply by measuring the change in one particular presentation (usually the one with the largest revenues). ²⁹

The top panel of the figure graphs the price indexes for sales through drugstores. Prices seem to be trending up in all three groups. This may be a particular feature of drugs which are about to go off patent, but it may also be attributable to the known fact that branded drug prices have been increasing more rapidly than generic drug prices. (The PPI we use reflects both branded and generic price changes.) Comparing across groups it appears that the trends for drugs in the low and medium entry probability groups are quite similar. In the preexpiration period prices for these drugs increase more slowly than the prices for drugs in the high entry probability group. Postexpiration their prices continue to rise while prices decline on average for drugs in the high entry probability group. There is no evidence in the graph of strategic price reductions in advance of entry by the drugs facing an intermediate entry probability.

To take another look for possible strategic price reductions, Table 12 reports on partitioning the drugs in each group according to whether the price change between the third and first year prior to patent expiration is greater or less than the change in the PPI for that period. Here we do see a nonmonotonic pattern. Forty five percent of the drugs in the medium entry probability group lower prices while this occurs for only twenty one percent of the drugs in the low entry probability group and twelve percent of the drugs in the high entry probability group.

²⁹We weight all drugs equally in computing mean price changes. When a patented drug is produced by two manufacturers it may contribute two observations to our indexes. One drug each was dropped from the hospital and drugstore indexes because small quantities sold meant that there were large rounding errors in our price data. We also dropped lotramin/gyne-lotramin from our medium entry probability hospital price index because it was a very large outlier (the price apparently increased by 200% between year -3 and year -2 and then was roughly constant for the remainder of the period.)
The bottom panel of figure 6 graphs price indexes for the hospital market. The data on hospital prices are much noisier—at the level of the individual drug the standard deviation of annual price changes is twice as large in the hospital market as in the drugstore market. The price indexes for hospitals tend to bounce around as a result, but again drugs in the low and medium probability groups appear to have similar trends. In this case, both price series increase fairly sharply throughout the period. Drugs in the high entry probability group appear to have slower price increases in the preexpiration period and to lower prices post expiration. Table 12 indicates that price decreases were most common among drugs facing an intermediate entry probability, but the differences between groups are very small and not statistically significant.

8 Conclusion

In this paper we have examined the behavior of pharmaceutical incumbents in advance of the opening of their markets to potential entrants. Our empirical approach has been motivated by the observation that the strategic incentive to deter entry may be strongest when incumbents face an intermediate probability of entry. We have carried out two types of analyses: looking at patterns in investment levels across drugs and looking at how firms change their behavior as the patent expiration date approaches.

Our analysis of investment levels yields little evidence of strategic entry deterring behavior. Strong direct effects of market size on the returns to journal advertising and presentation proliferation make it seem unlikely that we would find those variables to be nonmonotonic. Detail advertising displays much less in the way of scale effects, but we still find no evidence of detail advertising-to-sales ratios being unusually low in markets of intermediate size.

Our examinations of trends in advertising and product proliferation yield more interesting results. While the statistical significance varies with the particular set of results, in all three cases we estimate trends to be nonmonotonically related to the probability of generic entry. Detail advertising and journal advertising are both being reduced most rapidly prior to patent expiration among drugs which face an intermediate probability of entry. Presentation proliferation likewise seems to be increasing most rapidly among drugs facing an intermediate probability of entry.
References


The figure graphs the equilibrium advertising intensity in the model of section 2.3.1 where advertising raises consumers valuations both for the branded drug and for a generic substitute. The distribution of entry costs is assumed to be lognormal with mean 0.0025 and standard deviation 0.0015. The dotted line is the equilibrium advertising level when advertising is not observed until after firm 2's entry decision is made (and hence there is no entry deterrence motive.) The solid line is the equilibrium advertising level when advertising is observed in advance of the potential entry.
Figure 2: Equilibrium advertising levels in the model of differentiating advertising

The figure graphs the equilibrium advertising intensity in the model of advertising of section 2.3.2 when \( t = 0.25 \) and the distribution of entry costs is lognormal with mean 0.25 and standard deviation 0.25. The dotted line is the equilibrium advertising level when advertising is not observed until after firm 2’s entry decision is made (and hence there is no entry deterrence motive.) The solid line is the equilibrium advertising level when advertising is observed in advance of the potential entry.
Figure 3: Trends in detail advertising

The figure presents smoothed graphs of the mean time path of detail advertising for three groups of drugs over a four year period: the three year period prior to patent expiration and the year after patent expiration. Each graph has been normalized to begin at one in month -36. Drugs are classified as having a low, medium, or high predicted probability of entry depending on whether the predicted value from the regression reported on in table 3 is in [0, 0.3], (0.3, 0.8], or (0.8, 1]. The graphs are the fitted values from a kernel regression of \( 12 \) \( \text{Detail}_{it}/\text{Detail}_{jt} \) on a time trend using an Epanechnikov kernel with a window width of 10 months.
Figure 4: Trends in journal advertising

The figure presents smoothed graphs of the mean time path of journal advertising for over a four year period: the three year period prior to patent expiration and the year after patent expiration. Each graph has been normalized to begin at one in month -36. Drugs are classified as having a low, medium, or high predicted probability of entry depending on whether the predicted value from the regression reported on in table 3 is in \([0, 0.3]\), \((0.3, 0.8]\), or \((0.8, 1]\). Only the medium and high probability groups are graphed here. The graphs are the fitted values from a kernel regression of \(12J_{10i} / J_{13i}\) on a time trend using an Epanechnikov kernel with a window width of 10 months.
Figure 5: Trends in product proliferation

The figure graphs the mean in each year of a rescaling the Herfindahl index of the presentation-by-presentation revenues for each drug. The Herfindahl measure of proliferation has been rescaled (in the manner of a price index) so that it takes on a value of one for each drug in the third year prior to patent expiration. Decreases in the measure correspond to increases in the degree of proliferation. Means are presented for the three years prior to patent expiration, the year of patent expiration and the year following patent expiration for three groups of drugs. Drugs are classified as having a low, medium or high predicted probability of entry depending on whether the predicted value from the regression reported on in table 3 is in $[0, 0.3], (0.3, 0.8]$, or $(0.8, 1]$. 

Presentation Herfindahls

![Graph showing trends in product proliferation](image)
Figure 6: Price changes

The figure graphs price indices for the three years prior to patent expiration, the year of patent expiration and the year following patent expiration for three groups of drugs. Drugs are classified as having a low, medium or high predicted probability of entry depending on whether the predicted value from the regression reported on in table 3 is in \([0, 0.3]\), \((0.3, 0.8]\), or \((0.8, 1]\). The top panel contains price indices for sales to drugstores. The bottom panel contains price indices for sales to hospitals. Price changes for each drug are calculated from a single important presentation. Price changes are net of changes in the CPI for prescription pharmaceuticals. The price indices weight the drugs in each group equally.
Table 1: Variable names

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry3Yr</td>
<td>1 if at least one entrant within 3 years of patent expiration</td>
</tr>
<tr>
<td>EntryProb</td>
<td>Predicted entry probability</td>
</tr>
<tr>
<td>Chronic</td>
<td>0 if for acute illness, 1 if for chronic illness</td>
</tr>
<tr>
<td>HospFrac</td>
<td>Hospital fraction of revenue (for year prior to patent expiration)</td>
</tr>
<tr>
<td>Revenue3</td>
<td>Average annual revenue for three years prior to patent expiration</td>
</tr>
<tr>
<td>TherSubs</td>
<td>Number of other drugs in the therapeutic class</td>
</tr>
<tr>
<td>Detail</td>
<td>Monthly detailing advertising (000’s of minutes)</td>
</tr>
<tr>
<td>Journal</td>
<td>Monthly journal advertising expenditures (000’s of constant dollars)</td>
</tr>
<tr>
<td>Detail3</td>
<td>Average annual detailing in three years before patent expiration</td>
</tr>
<tr>
<td>Journal3</td>
<td>Average annual journal advertising in three years before patent expiration</td>
</tr>
<tr>
<td>PresHerf</td>
<td>HospFrac-weighted average of drugstore and hospital presentation Herfindahls</td>
</tr>
<tr>
<td>PresHerf3</td>
<td>Average of PresHerf in the three years before patent expiration</td>
</tr>
<tr>
<td>HPrice</td>
<td>Hospital price</td>
</tr>
<tr>
<td>DPrice</td>
<td>Drugstore price</td>
</tr>
</tbody>
</table>

The table describes the variables used in the analysis.

Table 2: Summary statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Observations</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry3Yr</td>
<td>63</td>
<td>0.59</td>
<td>0.50</td>
</tr>
<tr>
<td>Revenue3</td>
<td>63</td>
<td>39.355</td>
<td>55.754</td>
</tr>
<tr>
<td>HospFrac</td>
<td>63</td>
<td>0.21</td>
<td>0.30</td>
</tr>
<tr>
<td>Chronic</td>
<td>63</td>
<td>0.63</td>
<td>0.42</td>
</tr>
<tr>
<td>TherSubs</td>
<td>63</td>
<td>8.48</td>
<td>6.04</td>
</tr>
<tr>
<td>Detail3/Revenue3</td>
<td>69</td>
<td>0.005</td>
<td>0.008</td>
</tr>
<tr>
<td>Journal3/Revenue3</td>
<td>70</td>
<td>0.013</td>
<td>0.022</td>
</tr>
<tr>
<td>PresHerf</td>
<td>70</td>
<td>0.54</td>
<td>0.29</td>
</tr>
<tr>
<td>PresHerf3</td>
<td>70</td>
<td>0.54</td>
<td>0.29</td>
</tr>
<tr>
<td>DPrice/DPrice_{t-1}</td>
<td>245</td>
<td>1.019</td>
<td>0.067</td>
</tr>
<tr>
<td>HPrice/HPrice_{t-1}</td>
<td>233</td>
<td>1.010</td>
<td>0.129</td>
</tr>
</tbody>
</table>

The table presents summary statistics for some of the variables used in our analysis. The variables are described in Table 1.
Table 3: Entry equation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef. Estimate</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Revenue3)</td>
<td>0.76</td>
<td>0.20</td>
</tr>
<tr>
<td>HospFrac</td>
<td>1.03</td>
<td>0.78</td>
</tr>
<tr>
<td>Chronic</td>
<td>0.63</td>
<td>0.53</td>
</tr>
<tr>
<td>log(TherSubs)</td>
<td>0.02</td>
<td>0.29</td>
</tr>
<tr>
<td>Constant</td>
<td>-7.60</td>
<td>1.94</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>63</td>
<td></td>
</tr>
<tr>
<td>PseudoR²</td>
<td>0.43</td>
<td></td>
</tr>
</tbody>
</table>

The table presents estimates from a probit model. The dependent variable is a dummy for whether entry occurs within three years of patent expiration. The explanatory variables are average revenue in the three years prior to patent expiration, the fraction of sales which are through hospitals (as opposed to drugstores), a measure of whether the drug treats a chronic or acute condition, and the number of other drugs in the therapeutic class. The observations are 63 drug molecules which lost patent protection at some point between 1986 and 1992.

Table 4: Advertising intensity versus predicted entry probability

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Dependent variable:</th>
<th>Dependent variable:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Detail Advertising</td>
<td>Journal Advertising</td>
</tr>
<tr>
<td>EntryProb</td>
<td>0.003</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>f(EntryProb)</td>
<td>-0.003</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.004</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>69</td>
<td>70</td>
</tr>
<tr>
<td>R²</td>
<td>0.04</td>
<td>0.07</td>
</tr>
</tbody>
</table>

The table reports coefficient estimates from linear regressions of two advertising-to-sales ratios on the predicted attractiveness of drug markets to potential entrants. Here, $f(x) = e^{-(x-1)^2/0.2^2}$. The first column examines detail advertising. The second examines journal advertising. Standard errors are in parentheses. The units of observation are 70 branded drugs which lost patent protection between 1986 and 1992.
Table 5: Means of advertising variables by entry probability

<table>
<thead>
<tr>
<th></th>
<th>Predicted Entry Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Mean of $\text{Detail3/Revenue3}$</td>
<td>0.0040</td>
</tr>
<tr>
<td>Mean of $\text{Journal3/Revenue3}$</td>
<td>0.0080</td>
</tr>
</tbody>
</table>

The table reports the means of two advertising measures within the groups of drugs with low, medium and high entry probabilities: the ratio of detailing minutes to sales and the ratio of journal advertising expenditures to sales. Drugs are classified as having a low, medium or high predicted probability of entry depending on whether the predicted value from the regression reported on in table 3 is in $[0, 0.3], (0.3, 0.8],$ or $(0.8, 1]$.

Table 6: Changes in advertising prior to patent expiration

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>$\text{Detail3}_{i,t}^{-1}$</th>
<th>$\text{Detail3}_{i,t}$</th>
<th>$\text{Journal3}_{i,t}^{-1}$</th>
<th>$\text{Journal3}_{i,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{LowEntryProb1Time}_t$</td>
<td>-0.007</td>
<td>-0.042</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.033)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{MidEntryProb1Time}_t$</td>
<td>-0.032</td>
<td>-0.024</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{HiEntryProb1Time}_t$</td>
<td>0.009</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{Time}_t$</td>
<td>-0.0003</td>
<td>-0.049</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.043)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{EntryProb1Time}_t$</td>
<td>0.014</td>
<td>-0.044</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.047)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$f(\text{EntryProb1})\text{Time}_t$</td>
<td>-0.050</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.025)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>1836</td>
<td>1836</td>
<td>1728</td>
<td>1728</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
</tr>
</tbody>
</table>

The table reports estimates of the rate at which advertising expenditures change over time. The observations are monthly detailing minutes (journal advertising expenditures) over a three year period prior to patent expiration for 51 (48) drugs. Each dependent variable is scaled separately for each drug so that the mean value for each drug is one. The explanatory variables are a time trend (scaled to run from -1 to 1 over the 36 months prior to patent expiration) interacted with various functions of the predicted probability of generic entry. The function $f(x)$ is $e^{-(x-\frac{1}{2})^2/0.2^2}$. Robust standard errors allowing for within-drug correlations in the errors are in parentheses.
Table 7: Number of drugs which are increasing/decreasing advertising immediately prior to patent expiration

<table>
<thead>
<tr>
<th>Change in advertising in year prior to patent expiration</th>
<th>Predicted Entry Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Drugs with decrease in <em>Detail</em></td>
<td>3</td>
</tr>
<tr>
<td>Drugs with increase in <em>Detail</em></td>
<td>3</td>
</tr>
<tr>
<td>Drugs with decrease in <em>Journal</em></td>
<td>2</td>
</tr>
<tr>
<td>Drugs with increase in <em>Journal</em></td>
<td>1</td>
</tr>
</tbody>
</table>

The table reports the number of drugs in each entry-probability class for which the detail/journal advertising is lower/higher in the twelve months immediately prior to patent expiration than it was on average in the previous twenty four months. Drugs are classified as having a low, medium or high predicted probability of entry depending on whether the predicted value from the regression reported on in table 3 is in [0, 0.3], (0.3, 0.8], or (0.8, 1].

Table 8: Mean presentation Herfindahls by entry probability

<table>
<thead>
<tr>
<th>Predicted Entry Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
</tr>
<tr>
<td>Mean of <em>PresHerf3</em></td>
</tr>
</tbody>
</table>

The table reports the mean of the Herfindahl index of the presentation-by-presentation revenues for drugs within each group. Drugs are classified as having a low, medium or high predicted probability of entry depending on whether the predicted value from the regression reported on in table 3 is in [0, 0.3], (0.3, 0.8], or (0.8, 1].

Table 9: Presentation proliferation versus predicted entry probability

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Dep. Variable: <em>PresHerf3</em></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td><em>EntryProb</em></td>
<td>-0.41</td>
</tr>
<tr>
<td><em>f(EntryProb)</em></td>
<td>0.02</td>
</tr>
<tr>
<td><em>Constant</em></td>
<td>0.78</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>70</td>
</tr>
<tr>
<td><em>R^2</em></td>
<td>0.25</td>
</tr>
</tbody>
</table>

The table reports coefficient estimates from a linear regression of a measure of the degree to which incumbents have developed multiple presentations of their products on the predicted probability of generic entry. The dependent variable is the average Herfindahl index of the presentation-by-presentation revenues over the three years prior to patent expiration. The explanatory variables are, *EntryProb*, the predicted value from the regression in Table 3, and a nonlinear function of this variable, *f(EntryProb)*, where *f(x) = e^{-0.5(x-0.5)}/0.2^2*. The units of observation are 70 branded drugs which lost patent protection between 1986 and 1992.
Table 10: Changes in presentation Herfindahl prior to patent expiration

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Dependent variable: $\frac{PresHerf_t}{PresHerf_{t-3}} - 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>LowEntryProbTime$_t$</td>
<td>-0.008 (0.010)</td>
</tr>
<tr>
<td>MidEntryProbTime$_t$</td>
<td>-0.040 (0.015)</td>
</tr>
<tr>
<td>HiEntryProbTime$_t$</td>
<td>-0.017 (0.014)</td>
</tr>
<tr>
<td>Time$_t$</td>
<td>-0.005 (0.012)</td>
</tr>
<tr>
<td>EntryProbTime$_t$</td>
<td>-0.010 (0.020)</td>
</tr>
<tr>
<td>$f(EntryProb_t)Time_t$</td>
<td>-0.054 (0.029)</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>203</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.06 [0.06, 0.07]</td>
</tr>
</tbody>
</table>

The table reports estimates of the changes over time in the Herfindahl index of the presentation-by-presentation revenues in the three years prior to patent expiration. The data contain three annual observations for each of 70 drugs (with seven missing values). The dependent variable is scaled so that the mean value for each drug is one. The explanatory variables are a time trend (scaled to run from -1 to 1 over the three years prior to patent expiration) interacted with various functions of the predicted probability of generic entry. The function $f(x)$ is $e^{-(x-\frac{1}{2})^2/0.2^2}$. Robust standard errors allowing for within-drug serial correlation in the errors are in parentheses.

Table 11: Number of drugs which are increasing/decreasing presentation proliferation immediately prior to patent expiration

<table>
<thead>
<tr>
<th>Change in year prior to patent expiration relative to earlier years</th>
<th>Predicted Entry Probability</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drugs with decrease in $PresHerf$</td>
<td></td>
<td>5</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>Drugs with increase in $PresHerf$</td>
<td></td>
<td>5</td>
<td>6</td>
<td>16</td>
</tr>
</tbody>
</table>

The table reports the number of drugs in each entry-probability class for which the Herfindahl index of the presentation-by-presentation revenues, $PresHerf$, is lower/higher in the year immediately prior to patent expiration than it was on average in the previous two years. Ten drugs (eight in the low group) have no change in $PresHerf$. Data on $PresHerf$ in the year immediately prior to patent expiration is missing for two drugs. Drugs are classified as having a low, medium or high predicted probability of entry depending on whether the predicted value from the regression reported on in table 3 is in [0, 0.3], (0.3, 0.8], or (0.8, 1].
The table reports the number of drugs in each entry-probability class for which the change in price between the third and first year prior to patent expiration is less than or greater than the increase in the PPI for prescription pharmaceuticals.