Inferring the Effects of Vertical Integration from Entry Games

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January 17, 2008

Abstract

This paper presents a novel method of making inferences about the effects of vertical integration on firm profits and market outcomes. Starting with a game theoretic model of entry into a vertical oligopoly, I show that vertical rival effects contain information regarding how an increase in vertical integration affects the final good price. I estimate the vertical entry model using data from the US generic pharmaceutical industry. The estimates show that a vertical merger can have a significant effect on the post-entry profits of other firms. On the other hand, preliminary simulation results suggest that a vertical merger between potential entrants will not greatly alter the post-entry equilibrium market structure.

Introduction

The effect of vertical integration on market outcomes—such as prices, quantities, and product quality in the final goods market—can be either positive or negative. For instance, an increase in the level of vertical integration can lead to higher prices or lower prices in the downstream market, depending on the underlying demand and cost function parameters (Salinger [1988]; Hendricks and McAfee [2007]). This is because vertical integration has two countervailing effects: one is to decrease the integrating firm’s costs through the elimination of double marginalization, and the other is to raise the intermediate input costs faced by other non-integrated firms. In addition, vertical integration can have other motives such as facilitating noncontractible investments by alleviating hold-up problems between vertical segments, and assuring the supply of an intermediate good. Integration based on these motives will also affect market outcomes, but the direction of such effects is generally indeterminate.

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Because of these inherent indeterminacies, the motives for, and the effects of vertical integration tend to be analyzed on an industry-by-industry basis. The results of such studies are then used to inform competition policy as well as corporate strategy (Lafontaine and Slade [2006]).

This paper presents a novel method for empirically examining vertical integration in an individual industry. In contrast to most of the existing studies, the analysis does not rely on exogenous changes in vertical market structure. While the focus is on estimating the effects of vertical integration, the econometric model is also capable of shedding light on the motives for vertical integration.

The basic idea is to apply an econometric model of a static entry game to a vertical setting. By estimating firms’ payoff functions in a vertical entry game, it is possible to recover vertical rival effects—the effect of upstream, downstream, and vertically integrated rival entry on profits. These estimates can then be used to make inferences about the effect of increased vertical integration on market outcomes.

Perhaps more importantly, estimates of vertical rival effects can be used to analyze how a change in vertical structure among potential entrants (say, through a vertical merger) affects vertical market structures in post-entry equilibria. Existing studies have focused their attention on the relationship between vertical integration and market outcomes, *keeping constant the number of operating units in each vertical segment*. However, in some industries, a more relevant question may be whether or not the number of operating units changes as a result of vertical mergers.

To motivate the estimated model, I construct a model of simultaneous entry into a vertical oligopoly, characterized by heterogeneous firms and incomplete information. The theoretical model leads to an econometric model consisting of a mixed logit embedded into a two stage estimation model proposed by Bajari, Hong, Krainer, and Nekipelov [2006] and others.

I apply the vertical entry model to a dataset for the US generic pharmaceutical industry. This industry is characterized by a large number of markets for which it is possible to observe near-simultaneous entry. In addition, there is a clear demarcation between the upstream active pharmaceutical ingredient segment and the downstream finished formulation segment. Some generic pharmaceutical firms are vertically integrated while the others specialize in one of the segments. I find that an increase in vertical integration significantly reduces the post-entry profits of downstream-only entrants, upstream-only entrants, as well as other vertically integrated entrants. Comparative static results from the theoretical model suggest that such rival effects may contain information regarding the effect of a vertical mergers on the final good price.
The parameter estimates are subsequently used to simulate the effect of vertical mergers among potential entrants. Of particular interest is whether vertical mergers significantly alter the post-entry equilibrium configuration of firms. Although the simulation results are preliminary, they suggest that the changes in post-entry market structure due to mergers are likely to be small.

The remainder of the paper is structured as follows: In section I, I present a brief review of the empirical literature on vertical integration and that on market entry, and discuss how the two can be combined. In section II, I describe the vertical structure of the US generic pharmaceutical industry, and discuss the possible motives for and effects of vertical integration. The theoretical model is discussed in section III. In section IV, I describe the empirical strategy, followed by a description of the data in section V. Section VI presents the estimation results from the vertical oligopoly entry model. Section VII discusses the merger analysis, followed by a concluding section.

I Relationship to existing literature
I.1 Empirical analysis of vertical integration

Empirical studies of vertical integration can roughly be classified into those that investigate motivations, and those that focus on effects. Studies in the former group use firm-level cross section or panel data, observing how exogenous market and/or product characteristics relate to the incidence of vertical integration among firms. By testing whether certain types of markets tend to exhibit higher rates of vertical integration, these studies are able to infer the motivation for vertical integration. Recent examples include Woodruff [2001] on Mexican footwear manufacturers, Ciliberto [2006] on hospitals and physicians, and Baker and Hubbard [2004] on the trucking industry.

Studies that focus on the effects of vertical integration relate variation in vertical structure to market outcomes such as prices and product quality. Recent studies use panel data to exploit natural experiments—changes in vertical market structure that can plausibly be assumed to be exogenous. Notable examples in this group are Hastings and Gilbert [2006] on California gasoline markets and Suzuki [2006] on the cable TV industry.

Meanwhile, structural econometric models of vertical markets have recently been developed, including Villas-Boas and Zhao [2005], Villas-Boas [2007] and Hendricks and McAfee [2007]. These methods have the advantage of not having to rely on natural experiments, and being amenable to merger simulations (Lafontaine and Slade [2006]).
I.2 Empirical analysis of market entry

The empirical literature on static entry games has focused on the measurement of rival effects, or the effect of rival entrants on post-entry profits. Studies in this area have contributed to a better understanding of how oligopolistic firms behave. The starting point is the post-entry profit function for an oligopolistic firm, which has the number of entrants as an argument.

The basic econometric problem is that the number of entrants is an endogenous variable. Some of the earliest studies to tackle this econometric problem were Bresnahan and Reiss [1991a,b] and Berry [1992]. In Berry’s analysis of entry in the airline industry, each potential entrant’s post-entry profit is calculated from market and firm characteristics, the number of other entrants with positive profits (which forms a fixed point), candidate parameter values, and simulated draws corresponding to unobserved fixed entry costs. Based on these calculations, the number of firms with positive profits is counted, and plugged back into the profit functions. The parameter estimates are those that minimize the difference between the predicted number of entrants and the observed number of entrants.

Recently, Mazzeo [2002], Seim [2006], and Orhun [2005] have extended this framework to markets with product differentiation. In these studies, firms decide not only whether or not to enter a market, but also how or where to enter. Mazzeo [2002] considers highway-exit motel markets where operators decide among different quality levels. In Seim [2006] and Orhun [2005], stores choose among different locations. In all cases, the parameters of interest are those describing the effect that different types of rival entrants have on post-entry profits.

I.3 Using entry models to examine vertical integration

The differentiated-product entry models suggest a method of estimating the effects of vertical integration from entry data. Suppose we have data on entry into different markets, where each market consists of an upstream and a downstream segment. We can then estimate the post-entry profit equations of upstream-only firms, downstream-only firms, and vertically integrated firms, with the number of entrants of each type as the key explanatory variables. The coefficients on the number-of-entrants variables will inform us about vertical rival effects in this market. In section III, I argue that these rival effects may contain information regarding the impact of vertical integration on market outcomes.

The estimated parameters of a vertical entry model can also be used to investigate the effects of a vertical merger between potential entrants. For instance, suppose that we want to simulate a merger between two firms—one having relatively more upstream manufacturing capabilities and the other being more capable in downstream manufacturing. The merged firm
is likely to have a higher probability of entering as a vertically integrated firm, in comparison to the summed probabilities of the pre-merger entities. This means that the remaining firms will expect a higher number of vertically integrated firms in the post-entry equilibrium. Depending on the payoff function parameters, such a change in expectations may lead all potential entrants to alter their entry probabilities, possibly resulting in a different post-entry vertical market structure.

To the extent of my knowledge, the empirical horizontal entry model of Bresnahan and Reiss [1991a,b] and Berry [1992] has not extensively been utilized in merger analysis. This is perhaps due to the fact that these studies—which rely mainly on entry data—are not amenable to welfare calculations that require price and quantity information. Moreover, the horizontal entry model will likely only yield trivial predictions: that a merger will raise the entry probabilities of individual firms (since there will be one less potential entrant), but that the equilibrium market structure will mostly stay constant. On the other hand, the vertical entry model presented in this paper may be capable of producing nontrivial simulation results.

Another advantage of using empirical entry models is the possibility of testing more than one economic theory. The contribution of Berry [1992] was not only to develop a novel estimation method for entry games, but also to test theories of airport hubbing. He includes individual airlines’ pre-existing airport presence in each market as an explanatory variable in the post-entry profit function. The estimated coefficient on this variable gives the financial benefits of airport hubs. We can similarly examine the motives for vertical integration using entry data. Suppose we discover that a high value for a certain market characteristic is associated with high post-entry profits for vertically integrated firms, but not for downstream-only nor upstream-only firms. We can infer from this that the benefits of vertical integration is somehow related to that market characteristic.

II Vertical structure of the generic pharmaceutical industry

In the pharmaceutical industry, new drugs are developed by originator—also called brand-name or innovator—pharmaceutical companies. After a new drug loses patent protection, generic pharmaceutical companies can enter the market, offering products that are equivalent to the originator’s. Previous studies of the US pharmaceutical market have found that the price of generic drugs is much lower than that of brand-name drugs (Caves, Whinston, and Hurwitz [1991]). Some studies—such as Grabowski and Vernon [1992] and Frank and Salkever [1997]—have found that the price of the brand-name drug tends to increase in response to generic entry,
but most studies agree that the price of generic drugs is decreasing in the number of generic entrants (Reiffen and Ward [2005]).

The generic pharmaceutical industry has attracted the attention of economists, due to its important role in lowering healthcare costs as well as a peculiar feature: it is one of the few industries where it is possible to observe a large number of markets in which entry by multiple firms occurs almost simultaneously. In addition to the effect of generic entry on market prices, previous studies have looked at the determinants of market entry by individual firms (Scott Morton [1999]) and entry deterrence by originator pharmaceutical companies (Ellison and Ellison [2007]; Marco [2005]).

The generics industry is characterized by a clear demarcation between the upstream and downstream segments. The upstream segment manufactures active pharmaceutical ingredients, using basic and intermediate chemicals, solvents, catalysts, etc. as raw material. The downstream segment manufactures finished formulations by combining the active pharmaceutical ingredient with excipients, and processing them into dose forms such as tablets, capsules, and injectables.

The US generics market has traditionally been characterized by vertical separation of the upstream and downstream segments. This is because when the industry began to grow in the 1980s, high quality and low cost active ingredients were available from Italy and other countries that had weak patent laws at the time (Bryant [2004]). American generic drug companies such as Mylan and Barr chose not to manufacture active pharmaceutical ingredients in-house.

However, firms began to exhibit vertical integration during the 1990s. Foreign firms that used to only supply active pharmaceutical ingredients increasingly entered the finished formulation market. Examples of such firms are Teva of Israel and Ranbaxy of India. In recent years, the traditionally non-integrated US firms have also begun to acquire upstream assets, suggesting that a “bandwagon” effect is in progress1.

Today, most of the largest generic drug companies are vertically integrated to some extent. However, they differ in terms of where they have a larger presence. Mylan and Barr continue to be predominantly downstream firms. On the other hand, Ranbaxy, Dr. Reddy’s Laboratories, and other Indian firms have a larger presence in the upstream segment, while gradually expanding their downstream activities in the US.

The motives for vertical integration have been discussed in the industry press. A purchasing

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1Barr acquired the East European vertically integrated generic company Pliva, and Mylan acquired a majority stake in an Indian active pharmaceutical ingredient manufacturer called Matrix, both in September 2006. See Hart and Tirole [1990] for a discussion of bandwagon effects.
executive at Sandoz, one of the largest firms, mentions lower active ingredient costs, earlier access to active ingredients, and stability of supply as the advantages of vertical integration (Stafford [2006]). Others have mentioned the possibility that vertical integration allows better control over the information flow between segments, as well as better risk-sharing (Erdei [2004]; Hoffman [2004]).

On the other hand, there has been less discussion in the industry press over the effects of vertical integration on market outcomes. However, this does not automatically imply that the effects are likely to be benign. In the past, antitrust authorities have successfully challenged exclusive dealing contracts between the upstream and downstream segments of the generics industry\(^2\). Those cases have revealed that exclusivity can have a significant impact on prices\(^3\). While vertical integration in this industry has received less antitrust scrutiny compared to exclusive dealing, its effect on downstream market outcomes may be similar.

Each individual market in the US generic pharmaceutical industry corresponds to a drug product that has lost patent protection, and the scope of the market is nationwide. We do not find multiple isolated geographical markets for the same product, as in the gasoline and cable TV industries studied by Hastings and Gilbert [2006] and Suzuki [2006], respectively. Thus, the methodology of those studies—namely to exploit exogenous variation in vertical market structure across multiple markets for the same product—cannot be employed here. This is an additional motivation for the estimation method presented in this paper.

### III Model

Our empirical analysis is based on a two-stage game, played among potential entrant firms, of entry into a market consisting of an upstream and a downstream segment. In the first stage, firms decide whether or not to enter the market, as well as which vertical segment(s) to enter into. In the second stage, firms compete with rivals in their chosen segments, while trading with firms in the segment other than their own. In the following, I first discuss the specification of the post-entry game, focusing on the effect of vertical integration on market outcomes. Subsequently, I describe the entry game.


\(^3\)In Federal Trade Commission v. Mylan et al., the FTC argued that an exclusive dealing contract between Mylan, the downstream firm, and multiple upstream manufacturers regarding the active ingredients lorazepam and clorazepate led to retail price increases of between 1,900% and 3,200%!
III.1 Vertical integration and market outcomes

The objective of this sub-section is to demonstrate that, under a specific formulation for a vertical oligopoly, there is a logical relationship between the effect of vertical integration on the final good price on the one hand, and the effect of vertical integration on rival firm profits on the other.

The vertical oligopoly model of Salinger [1988] is one of “sequential Cournot”, with vertical market structure exogenously given by the parameters \{L, M, N\}. \(L\) is the number of downstream-only firms, \(M\) is the number of upstream-only firms, and \(N\) is the number of vertically integrated firms. Thus, the number of operating units in the downstream segment is \(L + N\), and the number of upstream operating units is \(M + N\). The upstream segment manufactures an intermediate good that is used by the downstream segment in fixed proportions to produce the final good. Specifically, each unit of the final good requires one unit of the intermediate good.

Market competition takes place in the following manner: First, upstream-only firms decide on the quantity of the intermediate good, according to the derived demand of the downstream segment. Next, downstream-only firms and vertically integrated firms choose the quantity of the final good according to the final demand curve, taking the intermediate good price as given. That is, upstream-only firms as a group have a first-mover advantage over downstream-only and vertically integrated firms. Moreover, downstream-only firms do not have any monopsony power in the intermediate good market\(^4\).

III.1.1 Basic setup

I assume that final demand is given by \(Q(p) = s(a - p)\) where \(p\) is the final good price, and \(a\) and \(s\) are parameters. I also assume that the marginal cost of manufacturing the intermediate good is constant at \(c\) with \(c < a\), and the marginal cost of transforming the intermediate good into the final good is zero. The profit maximization problems of the downstream firm and the vertically integrated firm can then be expressed as follows:

\[
\max_{q_D} \left( a - \frac{Q}{s} \right) q_D - wq_D
\]

\[
\max_{q_V} \left( a - \frac{Q}{s} \right) q_V - cq_V
\]

\(^4\)Gaudet and Long [1996] present a similar model, but where vertically integrated firms move simultaneously with the upstream-only firms.
where \( q \) is firm-level output, with subscripts \( D \) and \( V \) denoting “downstream-only” and “vertically integrated”, respectively; \( Q = Lq_D + Nq_V \) is total output in the final market; and \( w \) is the market price of the intermediate good. Taking the first-order conditions and solving for the symmetric-within-firm-type Nash equilibrium in the final market gives the following firm-level outputs:

\[
q_D = \frac{s[a - w - N(w - c)]}{L + N + 1}
\]

\[
q_V = \frac{s[a - c + L(w - c)]}{L + N + 1}
\]

The derived demand faced by the upstream-only firms is the summed output of the downstream-only firms, given by

\[
Q_D = Lq_D = \frac{sL[a - w - N(w - c)]}{L + N + 1}.
\]

This leads to the profit maximization problem of the upstream-only firm:

\[
\max q_U \left[ \frac{a + cN}{N + 1} - \frac{L + N + 1}{sL(N + 1)} Q_U \right] q_U - cq_U
\]

where the \( U \) subscript denotes “upstream only” and the term in square brackets is the inverse derived demand with \( Q_U = Mq_U \), and where I use the fact that \( Q_U = Q_D \) in equilibrium. Taking the first-order condition, we can solve for the equilibrium output of an upstream-only firm:

\[
q_U = \frac{s(a - c)L}{(L + N + 1)(M + 1)}.
\]

Plugging this into the inverse derived demand function yields the equilibrium price of the intermediate good.

\[
w(M, N) = c + \frac{a - c}{(M + 1)(N + 1)}
\]

Notice that the intermediate good price does not depend on the number of downstream-only firms. This is a result of the particular functional form assumptions, and not a generalizable result. Using the expression for \( w \), we can calculate the final good price and the post-entry
profits of downstream-only, upstream-only, and vertically integrated firms:

\[ p(L, M, N) = c + \frac{a - c}{L + N + 1} \left[ 1 + \frac{L}{(M + 1)(N + 1)} \right] \]  

(2)

\[ \pi_D(L, M, N) = \frac{s(a - c)^2}{(L + N + 1)^2} \left( \frac{M}{M + 1} \right)^2 \]  

(3)

\[ \pi_U(L, M, N) = \frac{s(a - c)^2L}{(L + N + 1)(M + 1)^2(N + 1)} \]  

(4)

\[ \pi_V(L, M, N) = \frac{s(a - c)^2}{(L + N + 1)^2} \left[ 1 + \frac{L}{(M + 1)(N + 1)} \right]^2 \]  

(5)

### III.1.2 Comparative statics

Salinger [1988] explores the impact of a vertical merger by conducting comparative statics on \( w(M, N) \) and \( p(L, M, N) \). Specifically, he examines the impact on prices of increasing the number of vertically integrated firms, while keeping constant the total number of operating units. This can be done by fixing the total number of downstream and upstream operating units at \( \bar{L} = L + N \) and \( \bar{M} = M + N \) respectively, and taking the derivative with respect to \( N \).

One of the main findings of Salinger [1988] is that the effect of vertical integration on market outcomes depends on the existing market structure. To see this, let us plug \( L = \bar{L} - N \) and \( M = \bar{M} - N \) into the price equations and differentiate with respect to \( N \):

\[ \frac{dw(N)}{dN} = \frac{(a - c)(2N - M)}{(M - N + 1)^2(N + 1)^2} \]  

(6)

\[ \frac{dp(N)}{dN} = \frac{(a - c)[(\bar{L} - N)(N + 1) - (\bar{L} + 1)(\bar{M} - N + 1)]}{(M - N + 1)^2(N + 1)^2} \]  

(7)

The sign of (6) depends on the sign of \( 2N - \bar{M} \): if \( N > \frac{\bar{M}}{2} \) or equivalently \( M > N \), then increased vertical integration leads to a higher \( w \); a phenomenon called “raising rivals’ costs” (Salop and Scheffman [1987]). However, a vertical merger does not lower consumer surplus unless \( p \) also rises. We can see that (7) is positive if and only if \((\bar{L} - N)(N + 1) > (\bar{L} + 1)(\bar{M} - N + 1)\). Substituting in the definitions of \( L \) and \( M \) leads to the condition \( L(N - M) > (M + 1)(N + 1) \). Thus, the conditions for raising rivals’ costs and the conditions for consumer surplus loss are different. This is in contrast to Ordover, Salop, and Saloner [1990], who find that an increase in the intermediate good price is always accompanied by an increase in the final good price.

Figure 1 shows the \( M-N \) plane for a fixed level of \( L \) \((L = 10)\). The plane is divided into
different regions according to the possibility of raising rivals’ costs and the possibility that the final good price rises. In the region above the 45 degree line, \( \frac{d\nu}{dN} > 0 \) so that rivals’ costs are raised. Meanwhile, \( \frac{dp}{dN} > 0 \) in the region above the curve defined by \( L(N-M) = (M+1)(N+1) \). It can be shown that when \( L > M + 1 \), this curve always lies above the 45 degree line\(^5\).

This result, due to Salinger [1988], shows that increased vertical integration can lead to higher final good prices when the number of upstream-only firms is less than the number of downstream-only firms, and the number of vertically integrated firms is sufficiently high. On the other hand, the final good price can fall as a result of increased vertical integration when these conditions are reversed. Thus, the effect of vertical integration on market outcomes is sensitive to the pre-existing market structure, and can vary across industries. This may explain why empirical studies have found evidence of the price-increasing effects of vertical integration in some industries—such as the gasoline industry studied by Hastings and Gilbert [2006]—but not in others.

I extend the basic result, and show that the direction of change in the final good price is closely related to the direction of change in firm profits as a result of a vertical merger. As before, we plug the definitions \( L = \bar{L} - N \) and \( M = \bar{M} - N \) into the profit equations (3)-(5), and take the derivative with respect to \( N \). These can be expressed as follows:

\[
\frac{d\pi_D(N)}{dN} = -\frac{2s(a-c)^2(M-N)}{(L+1)^2(M-N+1)^3}
\]

\[
\frac{d\pi_U(N)}{dN} = \frac{s(a-c)^2 \left[ 2(\bar{L} - N)(N+1) - (\bar{L} + 1)(M-N+1) \right]}{(L+1)(M-N+1)^3(N+1)^2}
\]

\[
\frac{d\pi_V(N)}{dN} = \frac{s(a-c)^2 \left[ (\bar{L} - N + (\bar{M} - N + 1)(N+1)) \left[ (\bar{L} - N)(N+1) - (\bar{L} + 1)(\bar{M} - N + 1) \right] \right]}{(L+1)^2(M-N+1)^3(N+1)^3}
\]

It can be seen from (8) that downstream-only firms are unambiguously hurt by a vertical merger. This makes intuitive sense, because a vertically integrated firm is not only a tougher competitor—due to the elimination of double marginalization—but it can also contribute to a rise in the intermediate good price faced by the downstream firm.

In contrast, the impact of a vertical merger on the profits of upstream-only firms and

\(^5\)The equation defining the curve can be rewritten as \( N = \frac{LM + M + 1}{L-M+1} \). Since \( N - M = \frac{(M+1)^2}{L-M+1} \), the curve always lies above the 45 degree line when \( M < L - 1 \). On the other hand, when \( M > L - 1 \) the curve always lies below the horizontal axis, and converges to \(-L-1\) as \( M \to \infty \). In this latter case, vertical integration causes the final good price to rise only in the region below the curve. Such a region is never entered, because the number of firms must be nonnegative.
vertically integrated firms depends on the pre-existing market structure. In the case of upstream-only firms, (9) shows that profits decrease in response to a vertical merger if and only if the following inequality holds: 

\[ 2(\tilde{L} - N)(N + 1) < (\tilde{L} + 1)(\tilde{M} - N + 1). \]

Using the definitions \( \tilde{L} = L + N \) and \( \tilde{M} = M + N \), the condition becomes \( 2L(N + 1) < (L + N + 1)(M + 1) \). Figure 1 shows the region on the \( M-N \) plane where this inequality is satisfied. Notice that the set \( \{(M, N) : \frac{d\pi_U}{dN} > 0\} \) and the set \( \{(M, N) : \frac{d\pi_U}{dN} < 0\} \) are mutually exclusive. This has important implications for empirical analysis: since \( \frac{d\pi_U}{dN} < 0 \) implies \( \frac{d\pi_U}{dN} < 0 \), a finding of a negative impact of increased vertical integration on upstream profits leads one to reject the hypothesis that a vertical merger is associated with higher final good prices, assuming that the linear Cournot model correctly describes the vertical oligopoly.

Turning to the profits of vertically integrated firms, (10) shows that profits increase in response to a vertical merger if and only if the following inequality holds: 

\[ (\tilde{L} - N)(N + 1) > (\tilde{L} + 1)(\tilde{M} - N + 1). \]

Interestingly, this condition is identical to the one for \( \frac{d\pi_U}{dN} > 0 \). Thus, if we find that increased vertical integration has a negative impact on the profits of firms that are themselves vertically integrated, we can reject the hypothesis that a vertical merger leads to higher final good prices.

The fact that the derivatives of firm profits with respect to \( N \) contain information on the price effects of a vertical merger turns out to be useful. This is because the effect of a vertical merger on profits can be expressed as a combination of rival effects: the effect of increasing the number of vertically integrated rivals by one, combined with the effect of decreasing the number of downstream-only and upstream-only firms by one each. Such rival effects can be estimated from market entry data, which tends to be more easily obtainable than price data. Thus, we can make inferences about the effect of a vertical merger on prices without using price data, and without having to rely on natural experiments.

### III.2 Entry game under incomplete information

Up to now, I assumed that market configurations are given exogenously. Here, I discuss how vertical market structures are formed endogenously. Ordover, Salop, and Saloner [1990] and Hart and Tirole [1990] consider the incentives for vertical mergers in the context of vertical duopoly. Gaudet and Long [1996] and Abiru, Nahata, Raychaudhuri, and Waterson [1998] extend this to the multiple firm case by incorporating a first-stage merger game into the sequential Cournot model: firms choose whether or not to vertically integrate in the first stage, and play sequential Cournot in the second stage. In these studies, the number of operating units in each segment is fixed.
Elberfeld [2002] assumes that firms play a first-stage *entry* game rather than a merger game. An entry game is more realistic than a merger game in industries characterized by multi-product firms and short product cycles. The generic pharmaceutical industry is a typical example of such an environment. In Elberfeld [2002], entry is sequential in segments: potential entrants first decide whether or not to enter as an upstream-only firm. Once the identity of upstream-only entrants are known, the remaining firms decide whether to enter as downstream-only firms, enter as vertically integrated firms, or not enter at all\(^6\). After all the entrants’ identities are known, the firms play sequential Cournot.

In contrast to Elberfeld [2002], I assume that each potential entrant simultaneously decides whether to enter as a downstream-only firm, an upstream-only firm, a vertically integrated firm, or not enter at all. After the market configuration is known, firms play a vertical oligopoly game such as the sequential Cournot. In the first-stage entry game, each firm’s action space is defined by the discrete set:

\[
\{\text{Not enter, Downstream only, Upstream only, Vertical integration}\}
\]

whose elements are abbreviated to \(NE, D, U,\) and \(V\) respectively. Payoffs are given by post-entry profits minus entry costs.

I make the additional assumption that firms are heterogeneous in their entry costs. Further, some part of the heterogenous entry costs is common knowledge among the potential entrants, while the remaining heterogeneity is private information. This assumption is motivated by the fact that in the generic pharmaceutical industry, the cost of developing a new product depends on factors that are potential sources of private information, but that are at least partially observable to rivals. These include the chemical synthesis capabilities of a firm, patented and unpatented technologies required for circumventing patents held by the originator, and knowledge regarding the suppliers of active ingredients and chemical intermediates.

Specifically, I assume that firm \(i\)’s entry costs can be written as follows:

\[
F_{iD} = f_D(Z_i) + \xi_D + \eta_{iD} \tag{11}
\]

\[
F_{iU} = f_U(Z_i) + \xi_U + \eta_{iU} \tag{12}
\]

\[
F_{iV} = f_V(Z_i) + \xi_D + \xi_U + \eta_{iV} \tag{13}
\]

\(^6\)Elberfeld [2002] also consider a case where all firms enter simultaneously, but where upstream-only entrants cannot switch to downstream-only or vertically integrated entry. In effect, this is similar to sequential entry.
where $Z_i$ is a vector of observables that enter into the functions $f_k(\cdot)$, $k = D, U, V$; $\xi_D$ and $\xi_U$ are downstream and upstream entry cost components that are common to all firms; and the $\eta$’s represent privately observed heterogeneity.

The entry process under incomplete information can be described as a static Bayesian game. The game is defined by players’ action spaces, type spaces, beliefs, and payoff functions. A pure strategy Bayesian Nash equilibrium is a set of strategies—mappings from type space to action space—that are mutual best responses (Gibbons [1992], p.148-151). Each mapping can be described by a set of “thresholds” that divide up the type space of a player into different regions, each region corresponding to a particular action to be taken by that player.

The Bayesian Nash equilibrium can be summarized as a mapping from choice probabilities to choice probabilities, in a system of equations such as the following (Aguirregabiria [2004]; Seim [2006]):

$$p = \Psi(p).$$

(14)

The vector $p$ consists of all the choice probabilities of all players; each element of $p$ represents the probability of a particular player taking a particular action.

To see why the Bayesian Nash equilibrium can be represented in this manner, suppose that player $i$ forms a conjecture about the thresholds of player $i'$, denoted $t_{i'}$. Since $i$’s belief regarding the private information of $i'$ is defined by a probability density whose support is the type space, player $i$ can use its conjecture of $t_{i'}$ to calculate the probability that player $i'$ chooses some action $k$. These subjective choice probabilities, calculated for every player $j \neq i$ and every action, are then used to form player $i$’s strategy—its own thresholds $t_i$. Meanwhile player $i'$ (along with all the other $j \neq i$) forms a conjecture regarding $t_i$ in order to subjectively calculate player $i$’s choice probabilities, which are then used to produce $t_{i'}$. In the Bayesian Nash equilibrium, the players’ conjectures regarding other players’ thresholds must be correct. Therefore, we can envisage a recursive process where choice probabilities are mapped to thresholds, and these thresholds are mapped back to choice probabilities. The function $\Psi(\cdot)$ embodies this recursive process.

Following Berry and Reiss [2007], if we can assume that the econometrician’s uncertainty regarding players’ heterogeneity corresponds exactly to the players’ uncertainty regarding other players, the system of equations (14) can be estimated as an econometric model of the static Bayesian game.

In the entry game context, the players are potential entrant firms. Each firm’s action space is $\{NE, D, U, V\}$, firm $i$’s type space is the set of all possible values of $(\eta_{iD}, \eta_{iU}, \eta_{iV})$, beliefs are
defined by the joint distributions over the \( \eta \)'s, and the payoffs are post-entry profits minus entry costs.

Suppose that post entry profits are given by \( \pi_D(L, M, N) \), \( \pi_U(L, M, N) \), and \( \pi_V(L, M, N) \), and that firm \( i \)'s entry costs are given by (11)-(13). Then, firm \( i \)'s thresholds are summarized by the following vector:

\[
t_i \equiv \left[ \begin{array}{c}
E[\pi_D(L, M, N)] - f_D(Z_i) - \xi_D \\
E[\pi_U(L, M, N)] - f_U(Z_i) - \xi_U \\
E[\pi_V(L, M, N)] - f_V(Z_i) - \xi_D - \xi_U
\end{array} \right] (15)
\]

The expectations are taken over the uncertain number of entrants \((L, M, N)\), and they are evaluated using \( i \)'s subjective probabilities regarding rivals’ entry decisions. These thresholds guide \( i \)'s entry decisions in the following way. Denoting \( t_i(n) \) as the \( n \)th element of \( t_i \), firm \( i \) chooses action \( D \) if and only if the following conditions hold:

\[
\eta_{iD} < t_i(1) \\
\eta_{iD} - \eta_{iU} < t_i(1) - t_i(2) \\
\eta_{iD} - \eta_{iV} < t_i(1) - t_i(3)
\]

Choice criteria for the other actions are defined analogously. Denoting the actual choice made by firm \( i \) as \( A_i \), the choice probabilities can then be calculated as follows:

\[
Pr(A_i = D) = Pr \left[ \eta_{iD} < t_i(1) \land \eta_{iD} - \eta_{iU} < t_i(1) - t_i(2) \land \eta_{iD} - \eta_{iV} < t_i(1) - t_i(3) \right] (16)
\]

\[
Pr(A_i = U) = Pr \left[ \eta_{iU} < t_i(2) \land \eta_{iD} - \eta_{iU} < t_i(2) - t_i(1) \land \eta_{iU} - \eta_{iV} < t_i(2) - t_i(3) \right] (17)
\]

\[
Pr(A_i = V) = Pr \left[ \eta_{iV} < t_i(3) \land \eta_{iV} - \eta_{iD} < t_i(3) - t_i(2) \land \eta_{iV} - \eta_{iU} < t_i(3) - t_i(1) \right] (18)
\]

\[
Pr(A_i = NE) = 1 - Pr(A_i = D) - Pr(A_i = U) - Pr(A_i = V) (19)
\]

**IV Econometric specification**

Using a sample of generic drug markets, I estimate the system of equations (14), where the choice probabilities are defined by equations (15)-(19).

I begin by specifying a functional form for the expected profits. I follow Seim [2006] and employ a linear approximation to the post-entry profit functions. Firm \( i \)'s expected net profits from entering market \( m \) as a downstream-only firm, entering as an upstream-only firm, entering
as a vertically integrated firm, and not entering can be written as follows:

\[
\Pi_{miD} = X_{mi}\beta_D + \delta_{DD}\left(1 + \sum_{j \neq i} Pr(A_{mj} = D)\right) + \delta_{DU}\sum_{j \neq i} Pr(A_{mj} = U) + \delta_{DV}\sum_{j \neq i} Pr(A_{mj} = V) + \alpha_{mD} + \epsilon_{miD}
\]  

(20)

\[
\Pi_{miU} = X_{mi}\beta_U + \delta_{UD}\sum_{j \neq i} Pr(A_{mj} = D) + \delta_{UU}\left(1 + \sum_{j \neq i} Pr(A_{mj} = U)\right) + \delta_{UV}\sum_{j \neq i} Pr(A_{mj} = V) + \alpha_{mU} + \epsilon_{miU}
\]  

(21)

\[
\Pi_{miV} = X_{mi}\beta_V + \delta_{VD}\sum_{j \neq i} Pr(A_{mj} = D) + \delta_{VV}\sum_{j \neq i} Pr(A_{mj} = V) + \delta_{UV}\left(1 + \sum_{j \neq i} Pr(A_{mj} = V)\right) + \alpha_{mU} + \alpha_{mV} + \epsilon_{miV}
\]  

(22)

\[
\Pi_{miNE} = 0
\]  

(23)

where \(X_{mi}\) is a matrix of explanatory variables containing the arguments of the post-entry profit function as well as the \(Z_i\) variables in (11)-(13). \(A_{mj}\) is the action chosen by firm \(j\) in market \(m\), and the \(\beta\)'s and \(\delta\)'s (rival effects) are the parameters to be estimated. The expectation operator in (15) passes through to the number-of-entrants variables due to the assumed linearity of post-entry profits. Moreover, the expected number of rival entrants \(E(L)\), \(E(M)\), and \(E(N)\) are simply the summed choice probabilities of the other firms. The \(\alpha\)'s are the negatives of the \(\xi\)'s in (11)-(13), and the \(\epsilon\)'s are similarly the negatives of the \(\eta\)'s.

I assume that the \(\epsilon\)'s are independently and identically distributed over alternatives and firms with the type I extreme value distribution. On the other hand, the \(\alpha\)'s are constant over firms within the same market. Across firms, they have a bivariate normal distribution with mean \([0 \ 0]^\top\) and covariance matrix \[
\begin{bmatrix}
\sigma_D^2 & 0 \\
0 & \sigma_U^2
\end{bmatrix}
\]. While the \(\xi\)'s in the theoretical model are common knowledge among firms, their empirical counterparts, the \(\alpha\)'s are unobservable to the econometrician. I assume that the \(\alpha\)'s are independent from the \(\epsilon\)'s, and treat them as error components whose distribution is to be estimated\(^8\).

\(^7\)From equations (3)-(5), we know that even in the simplest linear Cournot model, the post-entry profit functions are highly nonlinear in the number of entrants. Ideally, I would like to account for this nonlinearity by employing nonlinear transformations of the number-of-entrant variables. For example, Berry [1992] uses the log of the number of entrants in his study of a complete information entry game. As discussed by Aguirregabiria [2004], however, calculating the expected log of the number of entrants in the context of a Bayesian game creates a large computational burden. Moreover, in my case there are three number-of-entrants variables for which expectations must be calculated explicitly for each observation in the dataset. Even if I limit the sample to 10 potential entrants, calculating the expected logarithms involves the use of matrices with \(4^{10} = 1,048,576\) rows.\(^8\)

\(^8\)The assumption of a diagonal covariance matrix for the \(\alpha\)'s implies that the unobservable characteristics of the upstream and downstream segments of the same market are not correlated. This is a strong assumption which may affect the estimation results. An alternative is to allow the \(\alpha\)'s to have covariance matrix \[
\begin{bmatrix}
\sigma_D^2 & \sigma_{DU} \\
\sigma_{DU} & \sigma_U^2
\end{bmatrix}
\].
The extreme value distributional assumption enables us to write the choice probabilities of firm $i$ as follows:

$$\Pr(A_{mi} = D) = \frac{\exp(V_{miD}) + \alpha_{mD}}{1 + \exp(V_{miD}) + \exp(V_{miU}) + \exp(V_{miV}) + 2\alpha_{mD} + 2\alpha_{mU}}$$ \hspace{2cm} (24)$$

$$\Pr(A_{mi} = U) = \frac{\exp(V_{miU}) + \alpha_{mU}}{1 + \exp(V_{miD}) + \exp(V_{miU}) + \exp(V_{miV}) + 2\alpha_{mD} + 2\alpha_{mU}}$$ \hspace{2cm} (25)$$

$$\Pr(A_{mi} = V) = \frac{\exp(V_{miV}) + \alpha_{mD} + \alpha_{mU}}{1 + \exp(V_{miD}) + \exp(V_{miU}) + \exp(V_{miV}) + 2\alpha_{mD} + 2\alpha_{mU}}$$ \hspace{2cm} (26)$$

$$\Pr(A_{mi} = NE) = \frac{1}{1 + \exp(V_{miD}) + \exp(V_{miU}) + \exp(V_{miV}) + 2\alpha_{mD} + 2\alpha_{mU}}$$ \hspace{2cm} (27)$$

where $V_{miD}$, $V_{miU}$, and $V_{miV}$ are shorthand for the “deterministic” portion (i.e. the first four terms) of (20), (21), and (22), respectively.

The equations (24)-(27) may look like they can be estimated by multinomial logit. However, there are two complications. Firstly, the $V$’s contain the choice probabilities of other firms as arguments. These are not directly observed by the econometrician. Moreover, the choice probabilities form a fixed point of the system (14) when the underlying equilibrium is Bayesian Nash.

Secondly, the existence of the $\alpha$’s means that (24)-(27) are conditional probabilities; the $\alpha$’s must be integrated out before the system can be estimated. While they complicate the estimation, the $\alpha$’s play an important role econometrically. They help to alleviate the “independence of irrelevant alternatives” problem inherent in multinomial logit, and they control for unobserved heterogeneity across markets.

Seim [2006] resolved the first issue by placing a nested fixed-point algorithm within a maximum likelihood estimator. For each candidate value of the of the parameters, the vector of choice probabilities is solved as the fixed point of (14) before evaluating the likelihood function. Ahn and Manski [1993] and Bajari, Hong, Krainer, and Nekipelov [2006] take a different, two-stage approach: in the first stage, firms’ choice probabilities are estimated nonparametrically, without using the choices of other firms as explanatory variables. In the second stage, the first-stage estimates are used as explanatory variables.

I employ this latter, two-stage estimation method. The reason is that the vertical entry game is likely to have multiple equilibria.\footnote{Even in the simple two-firm case with heterogeneous entry costs and no private information, there could be multiple equilibria.} While it is possible to use a nested algorithm to find
all the fixed points for a given set of candidate parameter values, one is left with the question of how to choose among the fixed points. In contrast, the two stage method does not require one to find and choose among possible multiple equilibria. This is because the parameters are estimated under the assumption that they contain information on the equilibrium selection rule used by the firms (Bajari, Hong, Krainer, and Nekipelov [2006]).

In implementing the first stage, I estimate the firms’ choice probabilities nonparametrically, using each firm’s own characteristics and market characteristics as covariates in a multivariate kernel regression\(^ {10} \). In the second stage, the vector of choice probabilities generated in the first stage are used as explanatory variables.

In order to resolve the second complication of integrating out the \( \alpha \)'s, I estimate the system (24)-(27) as a mixed logit, using maximum simulated likelihood (Train [2003], chapter 6). Instead of integrating out the \( \alpha \)'s analytically or numerically, draws of \((\alpha^m_D, \alpha^m_U)\) are taken from a bivariate normal distribution with covariance matrix \[
\begin{pmatrix}
s^2_D & 0 \\
0 & s^2_U
\end{pmatrix}
\] (where the \( s \)'s are candidate parameter values), and plugged into the logit expressions. If \( R \) draws are taken, then for each market \( m \), the simulated likelihood contribution is calculated according to the following formula:

\[
SL_m = \frac{1}{R} \sum_{r=1}^{R} \prod_{i \in \Upsilon_m} \left( \frac{\exp(V_{miD}) + \alpha^r_{miD}}{1 + \exp(V_{miD}) + \exp(V_{miU}) + \exp(V_{miV}) + 2\alpha^r_{miD} + 2\alpha^r_{miU}} \right)^{d_{miD}} \times \left( \frac{\exp(V_{miU}) + \alpha^r_{miU}}{1 + \exp(V_{miD}) + \exp(V_{miU}) + \exp(V_{miV}) + 2\alpha^r_{miD} + 2\alpha^r_{miU}} \right)^{d_{miU}} \times \left( \frac{\exp(V_{miV}) + \alpha^r_{miV} + \alpha^r_{miD}}{1 + \exp(V_{miD}) + \exp(V_{miU}) + \exp(V_{miV}) + 2\alpha^r_{miD} + 2\alpha^r_{miU}} \right)^{d_{miV}} \times \left( \frac{1}{1 + \exp(V_{miD}) + \exp(V_{miU}) + \exp(V_{miV}) + 2\alpha^r_{miD} + 2\alpha^r_{miU}} \right)^{d_{miNE}}
\]

where \( r \) is the draw number. The maximum simulated likelihood estimates are obtained by maximizing the sum of the log of the simulated likelihood contributions:

\[
\hat{\theta} = \arg\max_{\theta} \sum_{m=1}^{M} \ln(SL_m)
\]

three pure strategy Nash equilibria in the vertical entry game: \((D, U), (V, NE), \) and \((NE, V)\).

\(^{10}\)Since the covariates include both discrete and continuous variables, I employ the discrete-continuous method of Racine and Li [2004].
where $\hat{\theta} = [\hat{\beta} \hat{\delta} \hat{\sigma}]$.

V Data

The model is estimated using data for the US generic pharmaceutical industry. The data consists of drug markets, each having an upstream segment manufacturing active pharmaceutical ingredients, and a downstream segment manufacturing finished formulations.

The markets are selected from a database of the US Food and Drug Administration (FDA) that contains the population of all drug approvals. I select a subset of drug markets in which the first approval of a generic drug took place between January 1, 1998 and December 31, 2005. I further narrow down to markets in which the relationship between the upstream and downstream segments is relatively straightforward. This leaves 69 downstream markets, each defined by a distinct active pharmaceutical ingredient and a distinct dosage form. The dosage form is either a tablet or a capsule. There are 69 corresponding upstream markets, each defined by a distinct active pharmaceutical ingredient. The Data Appendix contains further details on how the markets are selected, as well as a list of the drugs. The actual data was downloaded from a proprietary database called Horizon Global™, developed and maintained by Newport Strategies (part of Thomson Scientific).

I identify potential entrants as follows. Let us define $fdate_{id}$ as the first recorded downstream entry date of firm $i$ into any market, including those outside the sample. $ldate_{id}$ is similarly defined as firm $i$’s last recorded downstream entry date, and $edate_{mjd}$ is firm $i$’s date of entry into the downstream segment of market $m$. Firm $i$ is called a potential downstream entrant of market $m$ if $fdate_{id} \leq \min_j(edate_{mjD})$ and $ldate_{id} \geq \min_j(edate_{mjD}) - 365$, where $\min_j(edate_{mjD})$ is the date of first downstream entry into market $m$ by any firm. By subtracting 365 days from $\min_j(edate_{mjD})$ in the second inequality, I allow a firm to remain a potential downstream entrant for 1 year after its last entry. Similarly, firm $i$ is called a potential upstream entrant of market $m$ if $fdate_{iu} \leq \min_j(edate_{mjD})$ and $ldate_{iu} \geq \min_j(edate_{mjD}) - 1095$, where $fdate_{iu}$ is firm $i$’s first recorded upstream entry date and $ldate_{iu}$ is its last recorded upstream entry date. I subtract 1,095 days (3 years) from $\min_j(edate_{mjD})$ in the second inequality because upstream entry is sometimes recorded a few years before the generic market opens. Firm $i$ is called a potential vertically integrated entrant of market $m$ if and only if it is a potential downstream entrant as well as a potential upstream entrant.$^{11}$

$^{11}$It should be noted that my definition of potential entrants does not consider firms’ technological capabilities that are often required to enter particular pharmaceutical markets. For instance, the manufacture of several molecules in the HMG-CoA reductase inhibitor class (also called statins) require a fermentation process, which not all upstream firms are equipped to perform.
Using the above definition of potential entrants, and keeping only those firms that have actually entered at least two markets in the sample—either as a downstream-only, upstream-only, or vertically integrated firm—I obtain a dataset of 69 firms facing 4,489 choice situations. Each choice situation is a market-firm pair where a firm chooses whether or not to enter, and which segment(s) to enter. Not all choice situations involve the same choice set, because in a number of cases, the firm is a potential entrant in only one of the segments. Table 1 classifies the choice situations according to the alternatives faced, and the choices actually made.

The 69 firms do not form the population of generic pharmaceutical firms that were active during the observation period, nor do they form a random sample. The criterion that I apply—minimum of two entries within the sample—is motivated by the desire to capture rival effects accurately while keeping the estimation tractable. I justify the exclusion of smaller firms from the sample by assuming that they form a “fringe”, and are unlikely to generate significant rival effects. I do not have market share data, but documents relating to a recent merger case suggest that some generic drug markets are highly concentrated. In essence, all the large and medium-sized firms are included in the sample. Taken together, the 69 firms make up approximately 60% of the downstream entries in the population, and approximately 45% of the upstream entries in the population.

V.1 Entry indicator

Entry order is considered to be important in the generic pharmaceutical industry, because prices and profits fall rapidly in response to additional entry (Caves, Whinston, and Hurwitz [1991]; Reiffen and Ward [2005]). Therefore, it is reasonable to assume that most firms enter in the beginning stages of the market. However, it is difficult to define the exact beginning of a generic market. This is because many pharmaceutical markets continue to be covered by patents, even after the basic product patent on the active ingredient has expired. This gives rise to a situation where originator pharmaceutical firms and generic firms engage in patent litigation, and the timing of generic entry is partly determined by the outcome of such disputes. In addition, the Drug Price Competition and Patent Term Restoration Act of 1984 (also known as the Hatch-Waxman Act) provides a 6-month market exclusivity to the generic firm who is the first to file an application for marketing approval, and at the same time challenges a originator firm’s

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12 In a study of rival effects in the UK hamburger market, Toivanen and Waterson [2005] use data on only two firms, McDonald’s and Burger King. Even though other firms exist, they are not considered to wield significant strategic effects.

13 See Federal Trade Commission: In the matter of Teva Pharmaceutical Industries and IVAX Corporation, Docket No. C-4155, complaint filed January 20, 2006. It is stated that Teva and IVAX have a combined market share above 50% for several products.
patent on invalidity or non-infringement grounds. Other generic firms who are not first-to-file must wait until the exclusivity period expires before they can obtain approval from the Food and Drug Administration (FDA).

Figure 2 is a histogram of generic firms’ entry dates, counted as the number of days after the first generic entry. The sample contains the 69 firms in the sample, as well as other firms that experienced first generic entry between 1992 and 2005. It is apparent that a large proportion of entries occur within one month of the first generic entry date. There is also a mass of entries around the seventh and eighth months. This is likely caused by the 6-month generic exclusivity provision of the Hatch-Waxman Act.

According to the data for Figure 2, 56.1% of all generic entries occur within 1 year of the first generic entry date. The share rises to 73.3% if we expand the window to 2 years after the first generic entry. In the subsequent analysis, I employ the following definition of downstream entry: a generic firm is considered to have entered the downstream segment if its application for approval to market a generic finished formulation—called an Abbreviated New Drug Application (ANDA)—has been approved by the FDA within one year of the first ANDA approval in the same market.

In the upstream segment, firm $i$ is defined to have entered a market if it has submitted to the FDA a document—called a Drug Master File (DMF)—that describes how the firm manufactures the active pharmaceutical ingredient used in that market, and the submission is made before the first ANDA approval date. Both the upstream and downstream entries are identified from the regulatory records made public by the FDA.

The dependent variable is $A_{mi}$, firm $i$’s entry decision in market $m$. $A_{mi}$ is equal to $D$ when firm $i$ has received an ANDA approval for market $m$, but has not submitted a corresponding DMF. $A_{mi}$ equals $U$ when firm $i$ has not received ANDA approval, but it has submitted a DMF for the active ingredient used in market $m$. $A_{mi}$ is equal to $V$ when firm $i$ has both received ANDA approval and submitted a corresponding DMF. $A_{mi}$ takes the value of $NE$ when firm $i$ has neither received ANDA approval nor submitted a DMF for market $m$.

Table 2 shows summary statistics for the number of markets in the sample that a firm enters. On average, a firm in the sample enters 4 markets as a downstream-only firm, 3.3 markets as an upstream-only firm, and 0.87 markets as a vertically integrated firm. There are large disparities over firms, as seen from the standard deviation and the maximum number of entries per firm. The firm with the most total entries is Teva, with 25 downstream-only entries.

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Further details on ANDAs and DMFs are found in the Data Appendix.
5 upstream-only entries, and 14 vertically integrated entries.

The market with the highest number of entrants overall is that for fluoxetine hydrochloride capsules, with 10 downstream-only firms, 12 upstream-only firms, and 3 vertically integrated firms. Although the average number of vertically integrated firms is low, there are 9 markets out of 69 in which the number of vertically integrated entrants make up 25% or more of the total number of entrants.

V.2 Market characteristics
V.2.1 Market size

In the sequential Cournot model of vertical oligopoly, the post-entry profits of individual firms are unambiguously increasing in market size. This can be seen from the derivatives of the profit functions (3)-(5) with respect to the market size parameter \( s \), which are all positive. I measure market size by the total revenue for a drug in the US during the year prior to the first generic entry date. Logarithms of total revenue are taken, and named \( \log\text{-}\text{revenue} \).

I calculate the revenue figures from a publicly available data source called the Medical Expenditure Panel Survey (MEPS). MEPS is a large-scale annual survey of households co-sponsored by the Agency for Healthcare Research Quality and the National Center for Health Statistics. It has been conducted since 1996, asking respondents detailed information about their medical expenditures, and confirming those responses with the respondents’ pharmacies\(^{15}\). The public data consists of several different files, and one of them, called the Prescribed Medicines File contains information on the use and purchase of prescription drugs. As an example, in the 2004 Prescribed Medicines file (the latest year used in my study), there are a total of 317,065 records. Each record contains information on the quantity and other characteristics of the medicine such as its strength, and is assigned a sampling weight based on the MEPS stratified sampling scheme. I apply such weights to estimate the national total revenue for each drug in my sample, for the years 1996-2004. Despite its large sample size, the national revenues estimated from MEPS data fluctuate significantly across years, and this is probably due to sampling variability as mentioned in the MEPS documentation. I therefore take a two-year moving average of the estimated total revenue for each drug. Thus, the market size variable for year \( t \) is constructed as \( \frac{1}{2}(\log\text{-}\text{revenue}_t + \log\text{-}\text{revenue}_{t-1}) \), and the observation period is reduced to 1997-2004. This means that the market size variable is constructed for the years 1998-2005.

\(^{15}\)See Cohen, Monheit, Beauregard, Cohen, Lefkowitz, Potter, Sommers, Taylor, and Arnett [1996]. Other economics articles using the MEPS data include Lichtenberg [2001] and Rizzo and Zeckhauser [2005].
V.2.2 Patents

The second set of market characteristics pertains to patents. In the pharmaceutical industry, originator firms often file multiple patents for one product. In addition to the basic product patent covering the active pharmaceutical ingredient, there can be several secondary patents covering specific aspects, such as a process for manufacturing the active ingredient, a chemical form of the active ingredient, or a particular finished formulation. Such patents mostly arise during the drug development stage, after the drug compound has been discovered and patented, but prior to approval and marketing of the new drug. This implies that secondary patents generally expire at a later date than the basic patent, creating an entry barrier that the generic entrants must either accept, invalidate, or circumvent.

I construct two variables related to patents. The first is the number of product patents held by the originator firm (\textit{patent\_prod}). The first product patent to be filed is usually the basic patent, while the latter product patents cover specific forms of the active ingredient, such as alternative salts and polymorphs\footnote{A description of such secondary product patents—including a discussion of polymorphism—is found in Judge Richard Posner’s opinion in \textit{SmithKline Becham v. Apotex}, District Court, Northern District of Illinois, filed March 3, 2003.}. If a drug is protected by a secondary product patent, a generic entrant must either invalidate the patent or circumvent it—by manufacturing a novel unpatented form of the active ingredient, or an older unprotected form. Thus, a high number of product patents implies high fixed entry costs faced by the potential entrant.

The second patent variable is the number of process patents held by the originator (\textit{patent\_proc}). In general, a basic patent contains a claim for a manufacturing process, which goes into the public domain when the basic patent expires. However, the process disclosed in a basic patent is usually not suitable for commercial scale production; the originator firm patents alternative processes and uses one of them for actual production (Mándi [2003]). If this is the case, a generic entrant must circumvent all valid process patents. When there are many process patents covering a drug, upstream entry costs are likely to be higher.

In order to count the number of patents held by the originator firm by patent type, I must first identify the originator for each drug. Since there are sometimes multiple firms involved in the development of a single drug, it is difficult to identify a single firm as the originator. Moreover, new drugs are sometimes licensed out to other originator firms when marketing overseas, so that they are launched by different companies in different countries. To take account of the fact that originator pharmaceutical firms sometimes share launching rights across countries, I identify the \textit{launching firm} for each drug in the following countries: France, Germany, Japan, UK, and...
USA. I then search the Horizon Global database to find the US patents pertaining to the drug in question, held by each of the launching firms. The number of patents is then added up over launching firms to generate the patent variables.

Horizon Global contains a list of patents for most of the drugs marketed in the US. These patents are categorized into the following types: product patents, process patents, formulation patents, component-of-combination patents, new use patents, and general interest patents. Some of the patents are held by originator firms, some are held by generic firms, and some are held by specialist manufacturers supplying to the originator.

### V.3 Firm characteristics

Scott Morton [1999] finds that if a generic firm has more experience in manufacturing certain types of products—specific dosage forms or specific therapeutic groups—then that firm has a higher probability, relative to inexperienced firms, of entering into markets for drugs of the same type. Following her example, I construct a set of variables measuring a potential entrant’s manufacturing experience.

Suppose that firm $i$ faces an entry opportunity in market $m$. I define the variable $\text{exper}_\text{dose}\_\text{form}_{mi}$ as the number of downstream markets that firm $i$ has entered in the previous three years that were of the same dosage form as $m$. Past entries are not restricted to the 69 markets in the sample. The variable $\text{exper}_\text{dose}\_\text{thera}_{mi}$ is defined as the number of downstream markets of the same therapeutic category that were entered by firm $i$ in the previous three years.

Similar variables are constructed for the upstream segment. The variable $\text{exper}_\text{api}_{mi}$ is the number of active pharmaceutical ingredient markets that were entered into by firm $i$ in the previous three years, and $\text{exper}_\text{api}\_\text{thera}_{mi}$ is the proportion of those markets that were of the same therapeutic category as market $m$.

Not all of the estimated equations (20)-(22) contain all four experience variables: $\text{exper}_\text{dose}\_\text{form}_{mi}$ and $\text{exper}_\text{dose}\_\text{thera}_{mi}$ enter equations (20) and (22) while $\text{exper}_\text{api}_{mi}$ and $\text{exper}_\text{api}\_\text{thera}_{mi}$ enter equations (21) and (22). This is because downstream experience is not likely to affect upstream payoffs, and upstream experience is unlikely to have an impact on downstream payoffs. Moreover, such exclusion restrictions are recommended by Keane [1992] for simulation-assisted estimation in the context of multinomial probit. I have yet to confirm whether such exclusion restrictions are required for simulation-assisted estimation of mixed logit models. However, inclusion of the same set of variables in all three equations led to problems during esitimation, such as extremely high coefficient values. Table 3 presents the summary statistics for the explanatory variables.
VI Estimation results

I estimate the vertical entry game by embedding the mixed logit model within the two-stage procedure of Bajari, Hong, Krainer, and Nekipelov [2006]. The mixed logit specification takes into account unobserved heterogeneity across markets, which is likely to be significant in our empirical setting. The mixed logit model is estimated by maximum simulated likelihood, using 70 draws from a Halton sequence\(^{17}\).

Table 4 presents the parameter estimates. The three columns found in Tables 4 correspond to equations (20), (21), and (22). The columns represent the payoff functions of downstream-only firms, upstream-only firms, and vertically integrated firms, respectively. Before turning to the coefficient estimates, it may be noted that the variance of the error component \(\alpha_{Dm}\) is significantly greater than zero. This suggests the existence of significant unobserved heterogeneity across markets in the downstream segment. Even though \(\alpha_{Dm}\) and \(\alpha_{Um}\) are independent by construction, independence of irrelevant alternatives does not hold in this sample. This is because the error component entering equation \(V\) is \(\alpha_{Dm} + \alpha_{Um}\), whose covariance with \(\alpha_{Dm}\) is expressed as follows:

\[
\text{Cov}(\alpha_{Dm}, \alpha_{Dm} + \alpha_{Um}) = \sigma^2_D + \text{Cov}(\alpha_{Dm}, \alpha_{Um}) = \sigma^2_D,
\]

Thus, the use of the mixed logit specification to control for unobserved heterogeneity was justified.

VI.1 Effect of market characteristics

The market size variable \(\text{log revenue}\) is significant and positive in all three equations. This is in line with theoretical predictions, and conforms to the previous findings of Scott Morton [1999] for the same industry.

Turning to the patent variables, the number of originator product patents has a significant and negative coefficient in the downstream-only payoff equation. This suggests that product patents lower the entry incentive of downstream-only firms through the building of entry barriers. For the upstream-only and vertically integrated payoff equations, the coefficient point estimates for originator product and process patents are negative but not statistically significant. I tested

\(^{17}\)The Halton sequence is a popular non-random method for generating draws in simulation-based estimation. In comparison to pseudo-random generators, a Halton sequence provides better coverage of the support of the error component to be simulated. As a result, fewer draws are needed to achieve a given level of accuracy (Train [2003], chapter 9). I utilized Kenneth Train’s Matlab code for mixed logit, made public on the internet at http://elsa.berkeley.edu/ train/software.html.
whether the coefficients on the patent variables differ across equations, but the differences are not significant.

**VI.2 Effect of firm characteristics**

The experience variables all have the expected positive sign, and are statistically significant. A potential entrant faces higher downstream payoffs and higher vertically integrated payoffs when it has more experience manufacturing finished formulations of the same dosage form ($exper\_dose\_form$), or the same therapeutic category ($exper\_dose\_thera$). Similarly, experience in manufacturing active pharmaceutical ingredients ($exper\_api$) has a significantly positive effect on upstream payoffs as well as vertically integrated payoffs. Experience with active pharmaceutical ingredients in the same therapeutic category further increases payoffs, as seen from the positive and significant coefficients on the variable $exper\_api\_thera$. These coefficients are of a different order of magnitude compared to the other experience coefficients, because the variable is measured as a ratio rather than as a count.

The result that experience in similar markets leads to higher payoffs agrees with the findings of Scott Morton [1999]. While experience lowers entry costs in Scott Morton’s model, here it either lowers entry costs, raises post-entry profits, or both.

**VI.3 Rival effects**

The $\delta$ estimates correspond to the rival effects discussed in subsection III.1.2. Several of the $\delta$s are statistically significant. Starting with same-type rival effects, we find that the effect of downstream-only entrants on downstream-only payoffs and the effect of vertically integrated entrants on vertically integrated payoffs are both significantly negative, as predicted by theory. On the other hand, the significant and positive impact of upstream-only entrants on upstream-only payoffs is counterintuitive, and defies explanation. Turning to cross-type rival effects, a $ceteris\ paribus$ increase in the number of upstream entrants raises downstream payoffs. This is presumably because more upstream competition leads to lower input costs for downstream firms. A $ceteris\ paribus$ increase in the number of vertically integrated entrants, on the other hand, leads to a decrease in downstream payoffs. This implies that the increase in downstream rivalry caused by a vertically integrated entrant overwhelms the benefits of upstream competition.

Following the discussion at the end of subsection III.1.2, we can analyze the impact of a vertical merger within the post-entry equilibrium by testing the following null hypotheses:
These equations represent the combined effect of increasing the number of vertically integrated entrants by one, and decreasing the numbers of downstream-only and upstream-only entrants by one each. These hypotheses allow tests of vertical foreclosure. For instance, if the null hypothesis in (29) is rejected in favor of the inequality \( \delta_{DV} < \delta_{DD} + \delta_{DU} \), then we can conclude that a vertical merger among the firms in the market will lower downstream payoffs.

Using the asymptotic covariance matrix of the parameters to conduct the tests, I find that the null hypothesis of (29) is strongly rejected in favor of the alternative, \( \delta_{DV} < \delta_{DD} + \delta_{DU} \)\(^\text{18}\). The remaining two null hypotheses are on the borderline of being rejected in favor of \( \delta_{UV} < \delta_{UD} + \delta_{UU} \) and \( \delta_{VV} < \delta_{VD} + \delta_{VU} \), respectively\(^\text{19}\).

Suppose we accept the discussion in III.1.2 that there is a logical relationship between the rival effect of a vertical merger on the one hand, and the effect of a the merger on prices on the other. Then, the above empirical findings seem to suggest that vertical mergers are not likely to raise the final good price in the generic pharmaceutical industry. However, since the theoretical results are based on a very specific model, and because the econometric model is not fully structural, it is better to refrain from making firm conclusions.

VII Application to vertical merger analysis

When two or more potential entrants in a vertical oligopoly merge, the post-merger, post-entry equilibrium may hold a different number of operating units—the number of upstream units and downstream units, counting each unit of a vertically integrated firm separately—as compared to the equilibrium that would have materialized were it not for the merger. The vertical mergers considered thus far in this paper are assumed to occur within the post-entry equilibrium. This may not be a relevant thought experiment if actual mergers that occur between potential entrants, prior to the market entry game, vastly alter the post-entry equilibrium.

Fortunately, the parameter estimates obtained from the vertical entry model can be used to simulate the effect of a merger between potential entrants, and see how the post-entry equiliubi-

\(^{18}\)The Wald statistic for \( H_0 \): (29) is 9.481, and the asymptotic \( t \) statistic is 3.079.

\(^{19}\)The Wald statistic is 3.2957 and 2.9251, respectively.
urm changes. Specifically, I first alter the dataset to imitate a vertical merger. This can be done by taking observations for two firms, and combining them to create a single observation. Next, the altered covariates and the parameter estimates are used to calculate the entry probabilities of every potential entrant in each segment, for all markets in the sample. The vector of entry probabilities forms a fixed point of equation (14), so that it can be recovered through numerical techniques. After obtaining the entry probabilities, they are added up to generate the expected number of entrants in each segment of each market.

As one such exercise, I simulate two simultaneous mergers. One is between Mylan, a US finished formulation manufacturer and Cipla, an Indian active pharmaceutical ingredient manufacturer. The second merger is between Barr, another US finished formulation firm, and Dr. Reddy’s, a vertically integrated Indian firm. I assumed that after the merger, the combined entity will have experience levels that are equal to the higher of the two merging parties. For example, suppose that Mylan has level 7 experience in formulation manufacturing and an active ingredient experience level of zero, while Cipla has zero formulation experience but an active ingredient experience of 10. Then, the hypothetical combined firm will simply be given level 7 formulation experience and level 10 active ingredient experience.

Using the altered dataset, I calculated the fixed-point entry probabilities by the method of successive approximations. After adding up the probabilities to obtain the expected number of entrants conditional on the merger, I compare the results with two benchmarks: the actual number of entrants, and the predicted number of entrants in the unaltered sample. The figures were calculated for each market, and results for in-sample drugs that went generic in years 2004 and 2005 are presented in Figure 3. The most notable thing about Figure 3 is that the expected post-entry market structures under the simulation is barely distinguishable from the predicted market structures in the original data. However, it appears that the simulated number of entrants is slightly fewer in all markets, a tendency that may partly be attributed to the one-firm decrease in the number of potential entrants. Nothing more can be said from these graphs, as I have not yet obtained standard errors for the simulated outcomes. Suffice it to say that the change in market structure due to the two mergers is not likely to be statistically significant.

Conclusion

I considered a model of simultaneous entry into an oligopolistic market consisting of a downstream and an upstream segment, and used it as a basis for estimating the effect of vertical integration in the US generic pharmaceutical market. If the vertical oligopoly is correctly de-
scribed by the Salinger [1988] model, then the effects of vertical integration on market outcomes can be inferred from estimates of rival effects—the effect of the number of entrants on post-entry profits.

Previous authors have estimated rival effects in static oligopoly games from entry data. By extending their methodology to a vertical context, I am able to estimate rival effects in a vertical oligopoly. My estimates for the US generic pharmaceutical industry indicate that a vertical merger can have significant negative effects on the payoffs of other firms. The vertical Cournot model would indicate that these results refute the existence of foreclosure effects. However, the assumptions underlying the vertical Cournot model—that downstream firms have no market power in the intermediate good market, and vertically integrated firms cannot buy or sell the intermediate good—are too strong to be realistic.

Meanwhile, the estimated parameters can be used to simulate the effect of a vertical merger between potential entrants. Of particular interest is the possibility of significant changes in post-entry market structure. While preliminary, the results of my simulation exercise suggest that vertical mergers are not likely to radically alter vertical market structures.

References


Table 1: Classification of Choice Situations

<table>
<thead>
<tr>
<th>Actual choice</th>
<th>Choice set</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>{NE, D}</td>
<td>{NE, U}</td>
<td>{NE, D, U, V}</td>
</tr>
<tr>
<td>NE</td>
<td>809</td>
<td>2,004</td>
<td>1,112</td>
</tr>
<tr>
<td>D</td>
<td>77</td>
<td>0</td>
<td>199</td>
</tr>
<tr>
<td>U</td>
<td>0</td>
<td>172</td>
<td>56</td>
</tr>
<tr>
<td>V</td>
<td>0</td>
<td>0</td>
<td>60</td>
</tr>
<tr>
<td>Total</td>
<td>886</td>
<td>2,176</td>
<td>1,427</td>
</tr>
</tbody>
</table>

**NE:** Not enter, **D:** Downstream-only, **U:** Upstream-only, **V:** Vertically integrated

The table shows the distribution of entry choices made by potential entrants. Firms are grouped according to the choice set they faced.

Downstream entry is defined as generic drugs that are approved within 1 year of the first generic entry date for the same market. The sample consists of 69 markets experiencing first generic entry between Jan. 1998 and Dec. 2005.
Table 2: Number of Entries Per Firm

(69 firms; 69 markets)

<table>
<thead>
<tr>
<th>Choice</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
<td>4.00</td>
<td>7.78</td>
<td>0</td>
<td>37</td>
</tr>
<tr>
<td>U</td>
<td>3.30</td>
<td>3.28</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>V</td>
<td>0.87</td>
<td>2.33</td>
<td>0</td>
<td>14</td>
</tr>
</tbody>
</table>

*D: Downstream-only, U: Upstream-only, V: Vertically integrated*

The table shows the number of sample markets entered by each firm. Entries are grouped according to the segment entered by the firm.
Table 3: Summary Statistics for Market and Firm Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Market characteristics (69 markets)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total revenue</td>
<td>333.45</td>
<td>546.00</td>
<td>0.90</td>
<td>2,667.38</td>
</tr>
<tr>
<td>(in million US dollars, 2000 prices)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log_revenue</td>
<td>18.46</td>
<td>1.75</td>
<td>13.71</td>
<td>21.70</td>
</tr>
<tr>
<td>patent_prod</td>
<td>1.97</td>
<td>2.58</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td>patent_proc</td>
<td>2.13</td>
<td>6.04</td>
<td>0</td>
<td>37</td>
</tr>
<tr>
<td><strong>Firm characteristics (4,489 choice situations)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>exper_dose_form</td>
<td>3.07</td>
<td>5.78</td>
<td>0</td>
<td>39</td>
</tr>
<tr>
<td>exper_dose_thera</td>
<td>1.70</td>
<td>3.46</td>
<td>0</td>
<td>29</td>
</tr>
<tr>
<td>exper_api</td>
<td>5.32</td>
<td>7.05</td>
<td>0</td>
<td>51</td>
</tr>
<tr>
<td>exper_api_thera</td>
<td>0.02</td>
<td>0.04</td>
<td>0</td>
<td>0.47</td>
</tr>
</tbody>
</table>

log_revenue: logarithm of total US revenue in year before generic entry

patent_prod: number of product patents held by the originator firm

patent_proc: number of process patents held by the originator firm

exper_dose_form: number of downstream markets of the same dosage form entered by firm in previous 3 years

exper_dose_thera: number of downstream markets of the same therapeutic category entered by firm in previous 3 years

exper_api: number of upstream active pharmaceutical ingredient markets entered by firm in previous 3 years

exper_api_thera: proportion of upstream markets entered in previous 3 years that were of the same therapeutic category

35
<table>
<thead>
<tr>
<th></th>
<th>downstream (D)</th>
<th>upstream (U)</th>
<th>vertical (V)</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>-16.9967</td>
<td>-8.5062</td>
<td>-18.8131</td>
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<tr>
<td></td>
<td>(2.6102)</td>
<td>(1.3906)</td>
<td>(4.0491)</td>
</tr>
<tr>
<td>log_revenue</td>
<td>0.7689</td>
<td>0.2755</td>
<td>0.8085</td>
</tr>
<tr>
<td></td>
<td>(0.1624)</td>
<td>(0.0849)</td>
<td>(0.2459)</td>
</tr>
<tr>
<td>patent_prod</td>
<td>-0.1677</td>
<td>-0.0445</td>
<td>-0.0928</td>
</tr>
<tr>
<td></td>
<td>(0.0727)</td>
<td>(0.0387)</td>
<td>(0.0979)</td>
</tr>
<tr>
<td>patent_proc</td>
<td>-0.0024</td>
<td>-0.0005</td>
<td>-0.0177</td>
</tr>
<tr>
<td></td>
<td>(0.0265)</td>
<td>(0.0120)</td>
<td>(0.0325)</td>
</tr>
<tr>
<td>exper_api</td>
<td>0.0349</td>
<td>0.0728</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0084)</td>
<td>(0.0135)</td>
<td></td>
</tr>
<tr>
<td>exper_api_thera</td>
<td>6.2668</td>
<td>7.4811</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.2059)</td>
<td>(2.3622)</td>
<td></td>
</tr>
<tr>
<td>exper_dose_form</td>
<td>0.1286</td>
<td>0.0604</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0137)</td>
<td>(0.0240)</td>
<td></td>
</tr>
<tr>
<td>exper_dose_thera</td>
<td>0.0941</td>
<td>0.0906</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0220)</td>
<td>(0.0337)</td>
<td></td>
</tr>
<tr>
<td>δ_{D}</td>
<td>-0.1411</td>
<td>-0.0469</td>
<td>-0.1304</td>
</tr>
<tr>
<td></td>
<td>(0.0849)</td>
<td>(0.0397)</td>
<td>(0.1082)</td>
</tr>
<tr>
<td>δ_{U}</td>
<td>0.3184</td>
<td>0.1634</td>
<td>-0.2370</td>
</tr>
<tr>
<td></td>
<td>(0.1517)</td>
<td>(0.0604)</td>
<td>(0.1847)</td>
</tr>
<tr>
<td>δ_{V}</td>
<td>-1.1710</td>
<td>-0.2408</td>
<td>-0.8700</td>
</tr>
<tr>
<td></td>
<td>(0.3398)</td>
<td>(0.1643)</td>
<td>(0.4664)</td>
</tr>
</tbody>
</table>

Error components

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>σ_{D}</td>
<td>0.8895</td>
</tr>
<tr>
<td></td>
<td>(0.1199)</td>
</tr>
<tr>
<td>σ_{U}</td>
<td>0.0157</td>
</tr>
<tr>
<td></td>
<td>(0.1612)</td>
</tr>
</tbody>
</table>

Number of observations 4,489
Log-likelihood -1611.12

log_revenue: log of total US revenue before generic entry
patent_prod: originator product patents; patent_proc: originator process patents
exper_api: upstream manufacturing experience
exper_api_thera: upstream manufacturing experience (% same therapeutic category)
exper_dose_form: downstream manufacturing experience (same form)
exper_dose_thera: downstream manufacturing experience (same therapeutic category)
δ_{D}: coefficient on number of downstream-only entrants • = D, U, V
δ_{U}: coefficient on number of upstream-only entrants • = D, U, V
δ_{V}: coefficient on number of vertically integrated entrants • = D, U, V
$L$: Number of downstream-only firms
$M$: Number of upstream-only firms
$N$: Number of vertically integrated firms

Vertical merger leads to higher final good price in $\frac{dp}{dN} > 0$ region
Vertical merger leads to higher intermediate good price in $\frac{dw}{dN} > 0$ region
Vertical merger leads to lower upstream profits in $\frac{d\pi_U}{dN} < 0$ region

Figure 1: Effect of increased vertical integration
Each bar measures the number of ANDA approvals (generic entrants) within a 30–day interval. Observations are pooled over 344 markets experiencing first generic entry in 1992–2005.

Figure 2: Distribution of Entry Timings of Generic Drugs
“Predicted number of entrants” was generated using the actual data.
“Simulated number of entrants” was generated after combining data for the following pairs of firms: Mylan and Cipla; Barr and Dr. Reddy’s.

Figure 3: Actual, Predicted, and Simulated Number of Entrants
Data Appendix

A.1 Market selection and entry indicators

The US Food and Drug Administration’s website provides a set of datafiles containing information on all pharmaceutical finished formulations that have ever been approved, including those that have been discontinued. Each approval is identified by a New Drug Application (NDA) number. From this database, known as the Orange Book, I first extract drugs that contain a single active pharmaceutical ingredient. This is because the relationship between the upstream active ingredient segment and the downstream finished formulation segment is simpler when there is only one active ingredient. Next, I keep drugs for which there is at least one generic approval—called an Abbreviated New Drug Application (ANDA) approval—and where the first generic approval occurs between January 1, 1998 and December 31, 2005.

Since many active ingredients are approved in multiple dosage forms, the relationship between the upstream and downstream segments is not always clear-cut even for single-ingredient drugs. For instance, the hypertension drug diltiazem hydrochloride is approved as a tablet as well as an injectable, but the active ingredient requirements for these two dosage forms are different (one is powder while the other is liquid); we are not able to discern from the data whether a given active ingredient manufacturer is supplying ingredients for tablets or for injectables.

I resolve this problem by limiting the downstream dataset to the first dosage form to be approved for each active ingredient. Moreover, I restrict the sample to tablets and capsules, not including extended-release or orally disintegrating formulations. This is because tablets and capsules are the two most common dosage forms, and are likely to make up a large proportion of the derived demand for active pharmaceutical ingredients. These restrictions lead to a downstream dataset consisting of 80 drugs, each with its own active pharmaceutical ingredient. After merging with the MEPS market size variables, the number of drugs with complete data is 69. Table A.1 presents a list of the drug in the sample.

The upstream dataset for these 69 drugs was constructed from the list of Drug Master Files.

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20These files are available from http://www.fda.gov/CDER/orange/obreadme.htm.

21Identifying generic approvals in the Orange Book is no simple matter. One way is to refer to the FDA’s online database, called Drugs@FDA (http://www.accessdata.fda.gov/scripts/cder/drugsatfda/index.cfm) which identifies generic approvals with the term “ANDA”. However, I have reason to believe that the FDA’s own classification is not immune to misclassification; several drugs approved prior to the year 1984 are classified as ANDA, even though abbreviated applications were not practiced until after the passage of the Drug Price Competition and Patent Term Restoration Act of 1984. Therefore, I use the FDA’s classification in conjunction with another classification method which I term the “trade name rule”. Under this rule, an approved drug is classified as generic if its trade name is the same as the generic name of the drug. After applying both rules, I visually inspect all approvals in the database to correct clear misclassifications.
(DMFs) published by the FDA on its website\textsuperscript{22}. A DMF is a dossier, submitted by an active pharmaceutical ingredient manufacturer to the FDA, containing detailed information regarding the manufacture of a particular product. The FDA refers to the contents of a DMF only when it reviews a New Drug Application for a finished formulation. An NDA—or an ANDA in the case of a generic product—contains the DMF identification number for the active ingredient being used, so that the FDA’s reviewing officer knows where to find the relevant information. Each entry in the FDA’s list of DMFs contains the names of the manufacturer and the product, as well as the submission date.

According to industry experts, a DMF submission does not always imply that the submitting firm is able to supply the active ingredient to the US market (Stafford [2006]). This is because the FDA neither approves nor rejects a DMF. A manufacturer may file a DMF in order to advertise that it is willing to supply a particular active pharmaceutical ingredient, but may not actually produce for the US market until buyer interest is confirmed. On the other hand, filing a spurious DMF that is not backed by actual production capability is potentially damaging to a manufacturer’s reputation. Moreover, changing the content of a DMF—say, in order to scale up to commercial production—is time-consuming, and requires the consent of customers. I take a DMF submission to indicate upstream entry, but minimize the risk of picking up spurious DMFs by restricting the dataset to manufacturers with 10 or more submissions.

\subsection*{A.2 Identifying firms and treating mergers}

By matching firms in the upstream and downstream datasets, it is possible to identify the vertical integration status of each entrant in each market. However, the FDA’s data on ANDAs and DMFs often contain multiple (sometimes erroneous) names for the same firm, and therefore must be cleaned extensively. Moreover, different firms belonging to the same corporate group are not identified as such.

To resolve this problem, I refer to the Horizon Global\textsuperscript{TM} database, which classifies finished formulation manufacturers and active ingredient manufacturers into uniquely defined corporate groups. I use Horizon Global’s corporate group classification to identify individual firms.

Since Horizon Global identifies the older ANDAs and DMFs in terms of their current corporate group affiliations, one must take into account the several mergers and acquisitions—both horizontal and vertical—that have taken place in the generics industry during the observation period and beyond. For instance, Teva and IVAX were rivals in both the API and finished formulation industries until IVAX was acquired by Teva in January 2006. Therefore, the two

\textsuperscript{22}The list is available at http://www.fda.gov/cder/dmf/.
firms should be treated as being separate before the acquisition. I gathered news information on the timings of mergers and acquisitions involving all firms in the sample, and created new corporate groups to describe the pre-M&A entities.
Table A.1: List of drugs in the sample

<table>
<thead>
<tr>
<th>Active pharmaceutical ingredient</th>
<th>Dosage form</th>
<th>Year of 1st generic entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>amiodarone hydrochloride</td>
<td>tablet</td>
<td>1998</td>
</tr>
<tr>
<td>amlodipine besylate</td>
<td>tablet</td>
<td>2005</td>
</tr>
<tr>
<td>azithromycin</td>
<td>tablet</td>
<td>2005</td>
</tr>
<tr>
<td>benazepril hydrochloride</td>
<td>tablet</td>
<td>2004</td>
</tr>
<tr>
<td>betaxolol hydrochloride</td>
<td>tablet</td>
<td>1999</td>
</tr>
<tr>
<td>bisoprolol fumarate</td>
<td>tablet</td>
<td>2000</td>
</tr>
<tr>
<td>bromocriptine mesylate</td>
<td>tablet</td>
<td>1998</td>
</tr>
<tr>
<td>buspropion hydrochloride</td>
<td>tablet</td>
<td>1999</td>
</tr>
<tr>
<td>buspirone hydrochloride</td>
<td>tablet</td>
<td>2001</td>
</tr>
<tr>
<td>cabergoline</td>
<td>tablet</td>
<td>2005</td>
</tr>
<tr>
<td>calcitriol</td>
<td>capsule</td>
<td>2001</td>
</tr>
<tr>
<td>cefprozil</td>
<td>tablet</td>
<td>2005</td>
</tr>
<tr>
<td>cefuroxime axetil</td>
<td>tablet</td>
<td>2002</td>
</tr>
<tr>
<td>cilostazol</td>
<td>tablet</td>
<td>2004</td>
</tr>
<tr>
<td>ciprofloxacin hydrochloride</td>
<td>tablet</td>
<td>2004</td>
</tr>
<tr>
<td>citalopram hydrobromide</td>
<td>tablet</td>
<td>2004</td>
</tr>
<tr>
<td>clarithromycin</td>
<td>tablet</td>
<td>2004</td>
</tr>
<tr>
<td>dantrolene sodium</td>
<td>capsule</td>
<td>2005</td>
</tr>
<tr>
<td>diclofenac potassium</td>
<td>tablet</td>
<td>1998</td>
</tr>
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