A fundamental question in industrial organization regards the relationship between price and the number of sellers. This relationship has been particularly important in the pharmaceutical industry where legislative changes were specifically designed to foster competition. Previous research on the pharmaceutical industry has shown generic entry has a mixed impact; generic prices fall rapidly with generic entry, whereas branded prices tend to increase or decrease only slightly. Using more complete data, focused on one segment of the pharmaceutical industry—anti-infectives—we find that the relationship between pharmaceutical prices and the number of sellers is more like that found in other industries. (*JEL L11, L65, D4*)

I. INTRODUCTION

A fundamental question in industrial organization regards the relationship between price and the number of sellers ($N$). The interest in this issue has been rekindled by substantial recent work.¹ This article uses an extensive data set to provide an empirical analysis of the price–$N$ relationship for antiinfective pharmaceutical products.² The analysis shows that (1) prices fall rapidly moving from one seller to a few and (2) subsequent increases in the number of sellers continue to reduce prices, even when there are numerous sellers.³ Prices fall about 83% as the number of sellers increases from 1 to between 6 and 15, and fall by another 52% as sellers increase from the 6 to 15 range to more than 40. These results contrast with previous work on pharmaceuticals using more limited data and showing little impact of entry on branded prices.⁴ The results here indicate instead that the effect of an increase in number of sellers on prices in pharmaceuticals is similar to that found in other settings.

Pharmaceutical pricing behavior has attracted scrutiny from both policy makers and academic economists. As such, there have been a number of studies of pharmaceutical pricing behavior in general and the impact of generic entry on branded and generic drug prices in particular. Most of the previous studies have concentrated on small sets of drugs that have faced patent expiration across a number of therapeutic classes. Early studies focused on reduced form or semireduced form regression models that showed that branded prices and generic prices responded differently to generic entry. In particular, these studies showed that branded prices and generic prices responded differently to generic entry. In particular, these studies showed that branded prices responded little

¹See, for example, Applebaum (1982), Bresnahan (1981), Bresnahan and Reiss (1991), Caves et al. (1991), Porter (1993), Reiss and Spiller (1989), and Suslow (1986); portions of this literature are summarized in Bresnahan (1989).

²Although our analysis concentrates on the relationship between price and the number of firms, there has also been substantial work on the relationship between price and concentration.

³It should be noted that there is little if any price effect when the second generic enters, but price effects become significant as the third and fourth generics enter.

⁴The analysis here builds on Caves et al. (1991) and Grabowski and Vernon (1992) but covers a much larger set of products, including all 98 in the anti-infective category. In contrast, Caves and colleagues used 30 products and Grabowski and Vernon used only 18. Later studies also use limited numbers of products. Frank and Salkever (1997) have a sample of 45 drugs; Reifen and Ward (2002) uses 32 drugs. By using a larger number of products concentrated in a single therapeutic category, we hope to determine how prices are affected by the number of sellers for an entire group of products and avoid thorny problems associated with the heterogeneities in product use. The analysis here also provides a much more in-depth evaluation of the competition between branded and generics not found in these earlier investigations.
to generic entry, and in some studies even increased (see Caves et al., 1991; Grabowski and Vernon 1992; 1996). Frank and Salkover (1992) developed a theoretical model to explain the anomaly of rising branded prices in the face of generic competition. Their model posited a segmented market where there existed two groups of consumers—a quality-conscious segment that continues to buy the established branded product after generic entry and a price-conscious segment. Frank and Salkover show that because of the segmented nature of the market, entry likely makes the demand facing the branded manufacturer less elastic and thus leads to price increases. Frank and Salkover (1997) provide empirical tests and confirm that, consistent with the segmented markets theory, branded prices rise and generic prices fall in response to generic entry.

Finally, a number of studies have attempted to characterize the behavior of generic firms. Scott Morton (1999; 2000) finds that revenue in the years before patent expiration is the most important determinant of how many generic firms enter a given market. She also finds that generic firms tend to specialize in certain categories of products. Reifen and Ward (2002) develop a structural model of the response of generic prices to generic entry. This article investigates how prices decline as the number of sellers rises, evaluating the ability of formal theoretical models to organize the data. The results show that although existing models organize some of the data regarding price declines, there are important discrepancies between the data and existing models. We then characterize the differences between the data and the models, providing a basis for continued theoretical and empirical work.

There are a number of important differences between the data we use and those of previous researchers. First, unlike previous research on pharmaceutical pricing, our data are focused on a single therapeutic category—anti-infectives. This focus on a single therapeutic category provides a number of benefits, particularly with regard to controlling for cost differences and demand differences. Anti-infectives in particular is a useful category because they are primarily used for acute conditions, thus making demand conditions more uniform. In addition, because anti-infectives primarily treat acute conditions, and a single prescription is usually enough to treat a condition, prescriptions make a natural measure of quantity. However, anti-infectives are somewhat different from other therapeutic categories in that generic entry has historically been less costly than in other categories. The Abbreviated New Drug Application formula established by the Hatch-Waxman Act in 1984, which reduced the requirements for approval of generic products, had essentially been in place for decades for anti-infectives. As a result, although other categories did not see substantial generic entry until after 1984, anti-infectives had faced numerous generic entrants for some time. In addition, many anti-infective products, especially older ones, tend to be prescribed by generic name instead of the brand name, which hastens the acceptance of generic products.

These factors have led some researchers to predict that branded anti-infective prices may respond differently from those in other categories. Early empirical research seemed to confirm that result. Later empirical research has provided more mixed results, with some studies showing a pattern of rising branded anti-infective prices in the face of generic entry. Our results are more in line with the earlier studies, showing significant impact on branded prices from generic entry.

A second difference in our data is that they measure activity at the retail level. The use of retail prices raises two issues for our analysis. Previous research has pointed out that pharmacists may have a financial incentive to favor generic dispensing, especially since the advent of managed care (see Grabowski and Vernon 1996). However, our data end in 1990, when managed care was a much smaller factor than it is today. A second issue is to what extent retail prices can be used to analyze price competition among manufacturers. Given the intense

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5. Several studies note that the demand and supply conditions may be different for acute versus chronic drugs. See Lu and Comanor (1998), Scott Morton (1999, 2000).

6. Such acceptance may also occur because the U.S. Food certifies the manufacture of each batch of active ingredient for anti-infectives, but not necessarily for other drugs.

7. See in particular, Schwartzman (1976, chapter 12). See also Congressional Budget Office (1998, chapter 3).

8. Both Ellison (1998), and Griliches and Cockburn (1994) find that average branded anti-infective prices rise with generic entry, whereas Ellison et al. (1997) find significant responsiveness between branded and generic products.
competition among retail pharmacies, and the use of simple pricing rules that apply across most (if not all) drugs, price competition among manufacturers is likely to be reflected in retail level data.\footnote{The IMS data we use for our empirical analysis do not include rebates that are commonly paid by branded manufacturers to managed care. Congressional Budget Office (1998) notes that these rebates can continue and increase after generic entry, and thus not measuring them can obscure an important source of price competition for branded manufacturers. Note, however, that wholesale level data from IMS possess the same weakness, and to the extent that such rebates are important, our results underestimate the degree to which branded manufacturers respond to generic entry.}

The article also provides one of the few econometric analyses of product differentiation, including identifying separate effects on prices from increases in both generic and brand name competition. This analysis of competition between branded and generic products shows (1) that it is important to distinguish between branded products sold by other innovative firms besides the pioneer and unbranded entry by traditional generic manufacturers; (2) branded entry by other innovative firms has a different effect on pioneer prices than generic entry by strictly off-brand firms; and (3) there appears to be significant competition between generic and brand-name sellers, including the pioneer. Hence the results indicate that there are three distinctive product groups in pharmaceuticals: the pioneer, branded versions of the same molecule sold by other innovative firms, and ordinary generics, and there is significant price competition within and between these groups.

II. THE EMPIRICAL RELATIONSHIP BETWEEN PRICE AND NUMBER OF COMPETITORS

Aggregated Data

The data consist of retail-level pharmacy transaction data for all anti-infective products over the 1984–90 period.\footnote{The data were obtained from the National Prescription Audit of IMS America. Total expenditures and quantity data are collected from a stratified random sample of pharmacies and then used to construct nationwide retail sales estimates. In the present analysis, these monthly data have been aggregated into annual series, forming a panel data set where the unit of observations are annual data for an individual product sold by an individual company.} The data provide yearly observations on total expenditures and quantity of prescriptions sold for the individual sellers of anti-infective products. These data are used to construct an annual price per prescription for each seller of each product (detailed data appendix available on request). Attention is restricted to anti-infectives to control for units of measure, cost, and regulatory conditions across products. Doctors normally write an anti-infective prescription for a quantity of medication designed to cure a given infection. This practice makes the individual prescription the natural unit of measure for anti-infectives. For other pharmaceuticals, in contrast, a pill or a daily dose might be more relevant.\footnote{It should be noted that there may be different dosing and different presentations, e.g. liquid versus tablet, but that regardless of the dosing or presentation the standard practice is to write a prescription to cure the infection—which is why physicians tenaciously encourage patients to take all of the prescription.}

Food and Drug Administration testing and review standards are also the same within this class of products, so that regulatory costs and standards are also similar. Hence cost differences are likely small, and we can control adequately for different manufacturing techniques for different groups of products (see Caves et al., 1991; Grabowski and Vernon 1992; 1996).

We briefly review some summary statistics, a complete review is available in the data appendix (available on request). The average price (1982–84 dollars) in the sample is $10.29 with a standard deviation of $21.68. The smallest price is 0 and the largest price is $391.46.\footnote{The analysis introduces dummy variables for each class of products—for example, tetracyclines and penicillins—and also uses separate dummy variables for year of introduction that allows a flexible, nonparametric estimation of possible trends or other changes in cost over time, reflecting increased complexity due to more sophisticated molecules or changes in manufacturing techniques. These controls represent a significant improvement over previous work (see, e.g., Caves et al. 1991, who use a dummy variable by therapeutic class, which would be the same as imposing constant costs for all products in our sample).}

Attention is restricted to anti-infectives to control for units of measure, cost, and regulatory conditions across products. Doctors normally write an anti-infective prescription for a quantity of medication designed to cure a given infection. This practice makes the individual prescription the natural unit of measure for anti-infectives. For other pharmaceuticals, in contrast, a pill or a daily dose might be more relevant.\footnote{The reader should note that there are seven observations where total revenue is reported as zero and several observations where revenue is also extraordinarily high, both yielding outliers in pricing calculations. Reestimation without these observations does not qualitatively change the results.}

11. The active ingredients for these products are also commonly manufactured using identical equipment, making costs more similar for anti-infectives than across pharmaceuticals as a whole. Still, the analysis that follows introduces several control variables to allow for cost differences in a more sophisticated way than in previous work.\footnote{The reader should note that there are seven observations where total revenue is reported as zero and several observations where revenue is also extraordinarily high, both yielding outliers in pricing calculations. Reestimation without these observations does not qualitatively change the results.}
The average branded price (constant dollars) is $30.30 with a standard deviation of $45.77, and the average generic price (constant dollars) is $6.27 with a standard deviation of $6.91. The number of sellers for a given product varies from 1 (monopoly) to 61. The mean is 26.9 sellers. Our measure for the number of related sellers has a mean of 31.6 and ranges between 0 and 112. We also calculated the Herfindahl Hirschman index (HHI) for each chemical entity in each year. The mean HHI in the sample is 3,677, and the standard deviation is 2,669.

About 17% of the observations are for brand-name products, 13% are pioneer products. The number of observations is fairly evenly spread across the sample period and across IMS classifications. Erythromycins (14%) and cephalosporins (9.6%) contain the largest number of observations.

Almost half the observations (46%) are from drugs introduced before 1962. In other years, introductions vary from none in some years up to 8.4% of the sample in 1974. Thus the data set provides much detail and ample variation for the empirical tests that follow.

Anti-infective products are broadly categorized according to the general molecular structure of the central active chemical entity, such as penicillins, tetracyclines, erythromycins, and cephalosporins. These groups can be further disaggregated into specific molecular entities or combinations, and the analysis here focuses on the number of sellers of these individual products. Our data include 98 separately identified compounds. The analysis also considers competition among sellers of closely related molecules. Ellison et al. (1997) examine cross-product price competition in cephalosporins, and find mixed evidence of price competition across products for these closely related antibiotics. In contrast, Stern (1994) finds that in two of his four categories there is significant intermolecular substitution. Accordingly, in the econometrics we allow for intermolecular effects, though our results are more similar to Ellison et al. than to Stern.

Before turning to the theory and econometric specification, however, it is valuable to examine the simple relationship between price and number of sellers. Figure 1 presents these data. Although the econometric analysis uses individual prices for each seller in a panel data set, for clarity Figure 1 simply presents average prices, taking the mean price of all drugs with a particular number of sellers. The first point on the horizontal axis corresponds to drugs with one seller and the price is averaged over all such products in the sample, the second price is the average price for all two-seller drugs, and so forth.14 Figure 2 presents a similar view using HHI in place of numbers of competitors.

The two panels of Figure 1 present two different looks at the data. A shows average prices for all sellers, and B shows the average price for just the pioneers—the firms that originally developed the molecules. A shows a sharp drop in prices with the entry of the second through fifth sellers. Prices fall from the single seller price of more than $57 to $9.46 when there are five sellers. This rapid decline in prices continues throughout most of the relevant

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14. With 98 product categories and 7 years of data, there are 686 possible industry concentration outcomes. For example, there are 178 monopolies and 45 duopolies (90 price observations) making up the first two points in Figure 1.
range. B, focusing just on the prices of the pioneer developer, shows essentially the same pattern. Hence, these data show a decline in both overall average prices and prices of the pioneer developer.

The continuing price decline is well illustrated through a series of simple regressions of the price–N relationship, with progressive truncation of the sample on N from the left-hand side. These regressions permit one to assess the persistence of the inverse relationship between price and N. The results show that there is a statistically significant impact of the number of sellers on price, including when the sample is restricted to more than 30 sellers. 15 Hence there is a significant, continuing price decline in the reduced form that continues from only a few sellers to more than 40. Focusing just on the pioneer products, the results are highly similar. 16

We tried other specifications, and all the results are broadly similar. For instance, although our analysis concentrates on the price–N relationship, we also calculated the HHI for each of our 98 chemicals. The mean HHI was 3,677 with a standard deviation of 2,669. The range was 1,082 to 10,000. After constructing the HHI, we then replicated the regressions using the HHI in place of the number of firms. We ran a series of regressions,

15. The coefficient on the number of sellers in the simple price–N truncated regressions are as follows (t-statistics in parentheses): for regressions including all chemicals (N > 0), β = −0.47 (−21.42); for the regressions including only chemicals with five or more competitors (N ≥ 5), β = −0.15 (−14.213); for N ≥ 10, β = −0.13 (−14.46); for N ≥ 20, β = −0.15 (−13.38); N ≥ 30, β = −0.06 (−3.81); N ≥ 40, β = −0.01 (−0.43).

16. It should be noted that there is a single outlier for the pioneer products, which makes some difference in the results. There appear to be data problems with the prices for this drug, Vibramycin (PFizer: the pioneer doxycycline). If Vibramycin is included, the effect of N is insignificant for N ≥ 20, and significant and positive for N ≥ 30. With Vibramycin removed, the result is a significant negative coefficient for N ≥ 20 and negative but insignificant for N ≥ 30. We have not found other instances where Vibramycin swings results in this way or other similar outliers.
truncating the Herfindahl from above. The coefficient remained positive and significant, even when the regression was restricted to a HHI of less than 2,000. Thus, decreasing concentration reduces price, even for chemicals with very low HHIs.\(^17\)

It is unlikely that manufacturing cost differences explain the observed differences in price. Anti-infectives appear to exhibit constant marginal production costs, and manufacturing techniques are highly similar. There are differences in presentation, such as tablets, capsules, and suspensions, but these differences cut across products and groups of products. The one place where presentation could make a large, systematic difference is for intravenous drugs, which we investigate later. Hence manufacturing cost differences are unlikely to explain observed price differences. Still it is important to control carefully for costs and various other factors that might affect the observed price–\(N\) relationship, requiring a more detailed econometric investigation.

An Econometric Analysis of Oligopoly Models

To construct an econometric model of the relationship between price and the number of sellers, it is useful to rely on formal models to guide the analysis. The data summarized in Figure 1 show a continuous decline in price, ruling out a simple Bertrand model of price competition. Recognizing this, two simple alternative models of competition are the standard Cournot quantity setting model and the entry threshold model of Bresnahan and Reiss (1991). Standard Cournot oligopoly theory predicts that prices should initially fall quickly and then steadily approach marginal cost. A similar prediction is also provided by Bresnahan and Reiss’s entry threshold ratio method, which predicts a steady fall in variable profit margins. We compare the predictions of this simple Cournot model to the alternative of a simple linear relationship between price and the number of sellers and to a more general model that nests these alternatives.

To formalize the Cournot prediction, suppose a linear inverse demand of the form \(P(Q) = a - bQ\) with constant marginal cost, \(c < a\), and where \(Q\) represents total market output. With \(N\) identical sellers, the market price generated by the Cournot model takes the following familiar form:

\[
P^*(N) = (a + cN)/(N + 1).
\]

Note that the Cournot model predicts a linear relationship between price and roughly the inverse of the number of sellers.

The Cournot model only results in equation (1) when there is a linear demand and constant marginal cost. Constant cost is highly plausible for anti-infectives because the raw ingredients are manufactured in batches that are small relative to total output and pill making is constant cost. Linearity of demand, however, is a stronger assumption suggesting that one can think of (1) as a Cournot-like outcome rather than a structural test (see later discussion).

The Cournot model also assumes that firms are identical. For many of the chemicals in our analysis, especially those that have been off patent for a number of years, this assumption is plausible. The industry uses batch production technology characterized by constant returns to scale. For this reason, most of the previous literature in the field also uses the number of competitors as the key variable determining the competitiveness of prices (see Stern 1994; Ellison et al. 1997 for instance). Though the results reported use the number of competitors as the key variable, we also ran regressions using the HHI. The results are broadly similar to those reported. Thus the assumption of identical firms does not significantly affect the empirical results.

In our analysis \(N\) is the exogenous variable driving prices in equilibrium. We treat \(N\) as exogenously predetermined by market size and other factors in the previous period or periods, and price is then determined by the predetermined number of sellers in a particular period. Such an approach seems generally consistent with the data and with previous research on the determinants of generic entry (see Scott Morton 1999; 2000). For example, a regression of \(N\) on sales in the year before patent expiration (where data are available) shows that such sales explain more than

\(^{17}\) The coefficients on the HHI in the truncated regressions are as follows (\(t\)-statistics in parentheses): for the whole sample, 0.003 (24.54); restricting the sample to HHI < 5,000, 0.001 (11.48); for HHI < 3,000, 0.002 (5.214); for HHI < 2,000, 0.005 (6.97); for HHI < 1,000, no observations.
60% of variation of the number of sellers in the postpatent period. Hence ex ante market size is the key variable driving variation in \( N \).

It is also important to control for other factors that might affect prices. One key factor is possible competition from related products. Ellison et al. (1997) found little evidence to support such competition, and Stern (1994) finds such effects in some categories. To control for these effects we included the number of other sellers in the appropriate broader category of anti-infectives, such as penicillins, tetracyclines, and so forth. Brand recognition is also important, and we included a dummy variable for versions of the same molecule sold by other innovative companies that had achieved brand recognition. Below we undertake a more extensive analysis of branded, pioneer, and generic products. In contrast, different presentations of drugs do not differ sharply, except injectable products are systematically more expensive to manufacture and distribute. We introduced an IV dummy to control for these possible cost differences.

There are also potential cost and demand differences that require fixed effects to control for product age, product group, and year. Year of introduction fixed effects were included to control for differences in product age that could lead to differences in either demand or cost. For example, physicians sometimes use older products first in a course of therapy, potentially affecting demand and price. Alternatively there may be a trend where manufacturing costs of more recently developed products are higher due to the more advanced nature of the products. Individual year of introduction fixed effects provide a flexible procedure for accounting for such differences, and we will compare the results of using such fixed effects with a simple time trend.

In addition, products in different therapeutic subcategories may differ in manufacturing cost. Even though anti-infectives are generally manufactured using similar techniques, there could exist some differences across categories, such as tetracyclines or penicillins. Accordingly, we include fixed effects for these groups. Finally, fixed effects were included for individual sample years to control for changes in demand over time. The extensive use of fixed effects provides a much richer set of controls for cost and demand differences than the existing literature. For example, Caves et al. (1991) consider products across therapeutic categories (such as cardiovasculars versus anti-infectives) and simply use a single fixed effect for anti-infectives, which is equivalent to imposing a restriction that all of the fixed effects considered here are zero because the entire data set consists of anti-infectives. Hence the present study provides a large advance in the control of cost and demand factors in studying pharmaceutical pricing relationships.

We used weighted least squares because the cells for different numbers of sellers had sharply different variances. We used as weights the inverses of the estimated standard deviation of the residual for each value of the number of competitors. The results from the estimation are reported in Table 1. The results show general goodness of fit with a large \( F \)-statistic, \( R^2 \), and all of the key variables are highly significant.

The model derived from equation (1) does a good job of explaining the empirical relationship between price and the number of sellers of a given product. The results show that price is closely related to the inverse of the number of sellers of individual products, as predicted by the Cournot model. The parameter estimate for \( 1/(N + 1) \) is 28.70 with a \( t \)-statistic of 7.07. The parameter estimates indicate rapid price declines when a firm loses its (patent-protected) monopoly and faces competitors. A second seller drops prices by nearly $5, the third by $2.39, the fourth by about $1.43, and the fifth by about $0.97. These price effects, moreover, are large relative to the mean price in the sample of $10.29. Hence, when there are more sellers in a market the price falls sharply, but these price effects moderate quickly. Still, a significant though small effect continues far into the sample; going from 25 to 35 competitors is predicted to reduce prices in the structural model by $0.31, or about 7.5%.

It is worth noting several other results. First, the brand name variable shows an economically and statistically significant

18. This information on brand names was obtained from _Scientific American Medicine_. See section 3 for a more complete investigation of our definition of brand name and how brand name affects pricing and price competition.

19. The data appendix provides summary statistics for the various fixed effects.

20. This method implies that separate weights are calculated for each regression reported in the article. The results were not qualitatively affected by using a common set of weights, except as reported in the HHI regressions.
markup of $3.35 for brand-name products compared to generics. Because the mean price of generic products in the sample is slightly more than $6, this variable indicates roughly a 50% mark-up of brand-name products—products of other innovative firms—over generics.21 The variable representing intravenous products also shows a substantial price premium; the coefficient indicates that such products are priced at $13.11 more than other products, ceteris paribus.

Though the number of sellers of the compound in question (N) has a large effect on price, the number of sellers of related compounds (NR) has little effect. As noted, parameters predict a price decline of nearly $5 moving from monopoly to duopoly, and a rise in number of sellers from two to three cuts prices by another $2.50, and so forth. In contrast, the coefficient for sellers of related products is small, only 1.333, not quite significant at the 95% confidence level. Hence, these data suggest that price effects are driven primarily by changes in the number of sellers of the compound in question, where we concentrate the remainder of our analysis.22

Although we concentrate on sellers of individual chemicals, we do not interpret these chemicals as being separate markets. Instead, we take the weaker position that taking the number of sellers of related products into account makes little empirical difference. Hence it is appropriate to focus primary attention on sellers of individual products.

Before turning to the other specifications it is important to consider the fixed effects.23 The

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**TABLE 1**

Regression Results Based on the Cournot Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cournot Model (1)</th>
<th>Nested Model (2)</th>
<th>Linear Model (3)</th>
<th>HHI Model (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2.969</td>
<td>6.920</td>
<td>9.199</td>
<td>4.385</td>
</tr>
<tr>
<td></td>
<td>(12.350)</td>
<td>(7.142)</td>
<td>(11.422)</td>
<td>(8.600)</td>
</tr>
<tr>
<td>N / (N + 1)</td>
<td>28.698</td>
<td>18.534</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(7.067)</td>
<td>(3.783)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>HHI</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>(4.141)</td>
</tr>
<tr>
<td>N_R</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>(2.171)</td>
</tr>
<tr>
<td>1 / (N_R + 1)</td>
<td>1.333</td>
<td>1.234</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(1.938)</td>
<td>(1.746)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Intravenous products dummy</td>
<td>13.106</td>
<td>13.239</td>
<td>13.139</td>
<td>13.023</td>
</tr>
<tr>
<td></td>
<td>(18.916)</td>
<td>(19.207)</td>
<td>(19.025)</td>
<td>(18.203)</td>
</tr>
<tr>
<td>Mean dependent variable (weighted)</td>
<td>10.29</td>
<td>10.29</td>
<td>10.29</td>
<td>10.29</td>
</tr>
<tr>
<td></td>
<td>(1.48)</td>
<td>(1.48)</td>
<td>(1.42)</td>
<td>(1.40)</td>
</tr>
<tr>
<td>Observations</td>
<td>3168</td>
<td>3168</td>
<td>3168</td>
<td>3168</td>
</tr>
<tr>
<td>F-statistic</td>
<td>249.16</td>
<td>242.26</td>
<td>249.30</td>
<td>243.16</td>
</tr>
<tr>
<td>R^2</td>
<td>0.818</td>
<td>0.819</td>
<td>0.818</td>
<td>0.808</td>
</tr>
<tr>
<td>Root MSE</td>
<td>0.864</td>
<td>0.866</td>
<td>0.868</td>
<td>0.837</td>
</tr>
</tbody>
</table>

*Notes:* Dependent variable: real price per prescription. N = number of sellers. N_R = number of sellers of related products. HHI = Herfindahl index. *t*-statistics are in parentheses. Real price is in 1982–84 dollars. Regressions are weighted OLS. Weights are calculated by number of competitors and in each regression are equal to the standard deviation of the residual for each number of competitors. An appendix, available from the authors, contains the fixed effects results.

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21. The analysis in section III contains a more complete treatment of these issues.

22. Results with other specifications, such as using different functional forms for N and using the HHI in place of the number of firms, yield broadly similar results.

23. A complete tabulation of regression results, including the fixed effects, is available on request.
results show that only 9 of the 24 individual 
year of introduction fixed effects are statistically 
significantly different from the omitted 
median (1973) at the 5% confidence level. How-
ever, an $F$-test reveals that these effects are 
jointly significant at the 1% level ($F = 14.38$). 
Inspection of the coefficients shows that prior 
to 1973 all 11 are negative and after 1973 8 of 14 
are positive. Nevertheless, there does not exist a 
simple trend in that there is considerable var-
iation in the individual year fixed effects over 
time, showing that this method provides a 
highly flexible method for accounting for pos-
sible vintage effects.

The year of introduction dummies are 
cluded to control for vintage effects, such 
as increased quality for newer drugs, which 
Lichtenberg (2001) demonstrates is an impor-
tant attribute of newer drugs relative to older 
ones. To quantify these effects in a simple way, 
we also ran the regression using an age variable 
in place of year of introduction dummies. This 
procedure also permits us to test whether our 
more general treatment of vintage effects mate-
rially affected the results. Age is defined as 
years since introduction of the chemical. We 
also include age squared to account for poten-
tial nonlinear vintage effects. This parametric 
treatment of age is more restrictive than the 
year dummies defined and used because it 
constrains age effects to a quadratic form. The 
results, however, are essentially unchanged 
for all the key variables. These results also 
ensure that the specification of age effects 
does not account for any differences between 
the results here and those of other investiga-
tors. The estimate of the key coefficient on 
$1/(N + 1)$ in this specification is 37.18 with 
a $t$-statistic of 8.97. The coefficient for age 
is $-0.461$ with a $t$-statistic of $-7.14$. The 
squared term is small, 0.007, with a $t$-statistic 
of 5.70. For drugs that first entered the market 
during our sample period, the average first-
year price is $54.41. The quadratic age effects 
thus predict a fall in price of little more than 
13% over 40 years ($7.14$). This parametric 
approach suggests that systematic age effects 
for these products are small.

Turning to the therapeutic subcategory 
fixed effects, we omitted the median fixed effect 
for trimethoprim (IMS class 15500). Of the 
20 fixed effects for individual product groups, 
only 10 are statistically significantly different 
from this median. Even though the number of 
significant coefficients is small, the data do 
indicate significant differences across subcate-
gories because a joint test restricting these 
coefficients to zero is highly significant with an 
$F$-value of 58.16.

Finally, only three of the year fixed effects 
(1984–89) are significant at the 5% level. 
Furthermore, there is no distinct trend in the 
year coefficients, which indicates that the data 
do not suggest a simple trend in price over the 
sample period.

The fixed effects show that it is important to 
control for cost and demand conditions. The 
rich set of fixed effects shows substantial non-
linear variation by year of introduction, and 
there are generally small but significant differ-
ces in prices across subcategories. These 
fixed effects provide a significant improvement 
over existing work and control well for 
possible cost and demand differences. Hence 
the measured effect of competitors on price 
should not be the result of cost or demand 
differences.

Turning to the other specifications, an alter-
native to the highly nonlinear, inverse specifi-
cation of column (1) of Table 1 is a linear 
relationship. To test between these specifi-
cations, one can nest the two models including 
both the linear and nonlinear terms, as is done 
in column (2) of Table 1. The results for the 
nested model indicate that both terms are 
significant, suggesting that prices fall faster 
than the simple Cournot-like model would 
predict. Furthermore, although the linear terms 
are significant, they are economically small. 
For example, as the second firm enters, the 
primary model predicts a price decline of 
about $5, whereas the nested model predicts 
a somewhat slower price decline of just over 
$3; these differences are fairly small so that 
both models organize the data fairly well and 
in an economically similar way.

The most important difference between the 
nested model and the Cournot-like model 
regards their prediction of price declines when 
there are large numbers of firms. The nested 
model predicts a larger price decline when there 
are large numbers of firms and seems to 
capture better the empirical phenomenon of 
continuing price declines far into the sample. 
In fact, the linear term is roughly the same 
size as the coefficient in the simple regressions 
of price on $N$ when the sample is restricted to 
more than 30 sellers; hence, the linear term in 
the nested model enables it to capture the con-
tinuing price declines far into the sample.
Another difference occurs in the effect of the number of sellers of related compounds. In the inverse specification, these sellers have a marginally significant effect, whereas in the nested specification, these products have a statistically insignificant effect. The small size of these effects and their sensitivity to the specification may help explain the disparate findings of Stern (1994) and Ellison et al. (1997).

The third column of Table 1 shows the simple linear model without the nonlinear term, and the results are similar. The model exhibits large F-statistics and $R^2$ as in the other two specifications, and the coefficients of all explanatory variables are of the right sign and statistically significant. The key difference is that the linear model does not capture the sharp initial price decline that characterizes the Cournot and nested models.

Hence the results show a large impact of initial entry on prices of these various therapeutic compounds. This relationship is present, moreover, both in a simple reduced-form analysis and in an in-depth econometric analysis, where control is introduced for product age, potential manufacturing cost differences, the number of sellers of closely related products, and method of administration.24

We also ran these regressions with HHIs in place of the number of competitors. This regression is reported in the final column of Table 1. The results show a good fit, with an $R^2$ of 0.808, slightly less than for the regressions using number of sellers. The coefficient on the HHI for individual chemicals is positive and significant, indicating that decreasing concentration does reduce price. The coefficient on the HHI for the other chemicals in the IMS class is negative and significant, with a coefficient equal in size to that of its own chemical entity, indicating that decreased concentration in the broader class results in higher prices.

Because of this anomaly, we also ran the HHI regression (column [4]) with other HHI removed. The results were almost identical to those reported in Table 1, column (4) (the coefficient in this regression was also 0.0004, with $t = 4.816$). Thus, removing other HHI from the primary regression does not alter the results in any way. We also repeated the regressions in column (1) and (4) using the log of price as the dependent variable. The results are qualitatively unchanged.25

The price–N regressions and the price–HHI regression represent two competing linear models. Though we report results on both models, we conducted routine econometric tests to determine which model best explains the data. The results were inconclusive. One method to test these nonnested alternatives is to create an artificial nested model that includes both (HHI and other HHI) and $1/[1+N]$ and $1/[1+N_R]$ as independent variables along with all the control variables and then conduct an F-test on the HHI coefficients and the N coefficients (see Greene 1993, 222–23). The results indicate that neither specification can be rejected. The F-test that the coefficients on HHI and other HHI are both zero is 4.21. However, in this specification, the coefficient on HHI is not statistically significant (0.00009, with a t-statistic of 1.19), and the joint significance may be driven by the significance of the other HHI coefficient, which is negative (–0.0003, t-statistic = –2.21). The test that $1/(1+N)$ and $1/(1+N_R)$ are simultaneously zero is also easily rejected ($F(2,3110) = 21.69$). We also conducted a J-test of the two competing models to ensure that the results were not affected by the control variables (see Greene 1993, 223). Using the J-test, the hypothesis that the HHI model does not add any explanatory power cannot be rejected, and the symmetric hypothesis for the Cournot model is easily rejected. Thus, the J-test seems to favor using the inverse of the number of competitors as an independent variable over using HHI.

It is interesting to note the similarities and differences between these results and those in prior work. Perhaps the most closely related work in the literature on the price–N relationship is Bresnahan and Reiss (1991). They examine prices for dentists, auto repair shops, and the like in geographically isolated county seats. Their key finding was that the largest competitive impact occurs moving from two to three firms, another large impact moving

24. One limitation of the approach is that it imposes the Cournot model. A second alternative is to construct a general conjectural variations model which nests the Cournot conjecture and let the data determine if the Cournot conjecture can be rejected. We constructed such a model and found (using nonlinear least squares) that the Cournot conjecture could not be rejected.

25. An appendix containing the results of this regression is available on request.
from three to four, and smaller subsequent price impacts. They also argue that their inferred prices in relatively concentrated county seats remained considerably above those in “competitive urban markets.”

The analysis here shows a sharp price drop as the number of sellers increases from one to four or five and much smaller price effects thereafter, similar to their finding. Bresnahan and Reiss also find a significant difference between price estimates in concentrated (county seats) and unconcentrated (urban) markets. Their finding is consistent with our results, which show a continuing price decline as $N$ gets relatively large.

In contrast, the analysis here shows different results from those found in previous research on pharmaceuticals. Studies by Caves et al. (1991) and Grabowski and Vernon (1992) showed small branded price effects from entry. The results here show that pharmaceutical prices respond to an increase in the number of sellers similar to price responses found in other markets. There are several possible explanations for these differences in results.

Perhaps the most important is that the sample here is much larger than that used in these prior studies and contains much more variation in the number of sellers. In addition, we do not restrict attention to a short period following patent expiration but instead consider a variety of products with sharply different numbers of sellers. We also control more tightly for cost and demand differences. A different type of possibility is that the analysis here focuses on anti-infectives. Such a focus contributes to better control for cost and demand differences, but comes at the cost of a more narrow focus. For example, by concentrating on anti-infectives, the analysis focuses on products for which a single prescription is designed to cure, usage patterns are similar, and underlying cost conditions are likely more similar. These factors improve the econometrics but of course mean that extrapolation to other therapeutic categories must await further analysis.

The analysis corresponds to standard analyses of the price–$N$ relationship and prior studies of pharmaceutical pricing. The omission is that it does not take into account the differentiated nature of branded and unbranded products. We now turn to an explicit analysis of the differentiated nature of pharmaceutical products and the effect of such differentiation on pricing.

### III. PRODUCT DIFFERENTIATION AND PRICE COMPETITION

Considerably more can be learned about pricing by recognizing the differentiated nature of generic and brand-name products. Brand-name products generally attract quality-conscious customers, and generic firms compete over price. Competition within and between these segments can provide insight into pricing patterns and permits testing of specific models of competition between these groups.

One issue is to define a brand name, and there are two reasonable alternatives. One way is to categorize the original patent-protected product, defined hereafter as the pioneer, as the only brand name. A second way is to include products marketed by other innovative companies that are separately promoted and have achieved significant brand recognition even though they are not the pioneer. We evaluate both alternatives. To separate products with significant brand recognition, we categorized products specifically listed by brand name in the *Scientific American Textbook of Medicine*. These products are generally detailed to doctors in varying degrees and may or may not differ from more traditional generic entry.

Distinguishing between pioneers, brand names, and generics leads to several reduced form relationships between price and $N$. We are particularly interested in: (1) average brand-name prices and the total number of sellers, (2) average brand name prices and the number of brand name sellers, (3) average prices of pioneer products and the total number of sellers, and (4) average generic prices and the total number of sellers. These relationships are illustrated in the four panels of Figure 3. Panel A shows the relationship between average brand-name prices and the total number of sellers of a chemical. A shows that the price of brand-name drugs falls steadily with the number of competitors until there are roughly 25 to 30 competitors; afterward the point estimate indicates continued price declines, but the decline is no longer statistically significant.

Panel B of Figure 3 provides a different look at brand-name prices by showing how the average price of brand-name products is related to the number of brand name sellers of the chemical. The data show a considerable but irregular decline in price as the number of

26. Note that care must be used in interpreting these figures. For instance, the first point in B does not represent
brand name sellers rises. Panel C shows that prices of pioneers steadily decline as the number of sellers of the chemical rises. This panel is a repeat of Figure 1B. Note that the price decline exhibited here is much like that of Figure 1A. Finally, D presents data on average generic prices as related to the total number of competitors. The results show that for generic products prices fall steadily until there are more than 30 competitors.27

These data show that increases in the number of sellers of individual chemicals leads to price decreases over a large range, but the pattern of decrease and average price levels differ significantly for branded and generic products. For generics significant price effects continue far into the sample, whereas prices stabilize for brand names when there are large numbers of sellers.

We now turn to a more detailed econometric analysis of the competition between branded name and generic sellers of these products.

It is common in the industry to view brand-name products as being differentiated from their generic competitors. Pricing patterns after patent expiration and generic entry show that the price of the pioneer product remains much higher than the level of generic competitors for substantial periods of time. In fact, previous empirical studies have found that prices of pioneer products tend to rise after generic entry (see Grabowski and Vernon 1992; Masson and Steiner 1985). A useful way to approach competition between branded

27. The coefficients for the number of competitors is as follows (t-statistics in parentheses): For brand-name prices: $N > 0$, $\beta = -0.95$ (-8.93), $N \geq 10$, $\beta = -0.13$ (-3.84), $N \geq 20$, $\beta = -0.12$ (-2.62), $N \geq 30$, $\beta = -0.03$ (-0.38), $N \geq 40$, $\beta = -0.02$ (-0.13). For generic prices: $N > 0$, $-0.14$ (-16.71), $N \geq 5$, $-0.12$ (-14.17), $N \geq 10$, $-0.12$ (-13.78), $N \geq 20$, $-0.15$ (-13.84), $N \geq 30$, $-0.07$ (-4.40), $N \geq 40$, $-0.01$ (-0.38). For the HHI regressions, the coefficients are as follows. For brand names: overall, $\beta = 0.006$ (11.34); HHI $< 5,000$, $\beta = 0.001$ (2.88); HHI $< 4,000$, $\beta = 0.002$ (1.873), HHI $< 3,000$, $\beta = 0.002$ (1.584); HHI $< 2,000$, $\beta = 0.004$ (1.13). For generic prices: overall, $\beta = 0.0006$ (9.22), HHI $< 5,000$, $\beta = 0.001$ (10.72), HHI $< 4,000$, $\beta = 0.002$ (9.20), HHI $< 3,000$, $\beta = 0.002$ (5.34), HHI $< 2,000$, $\beta = 0.006$ (7.23).
and generic products is to view them as differentiated products. In this setting, additional generic entry should have a larger impact on generic prices than on brand-name prices because entry is taking place closer to existing generic competitors in product space. Table 2 presents several specifications of the relationship between price declines for branded and generic drugs. Because generic drugs are likely to compete more closely with each other than with branded products, one might expect branded prices to fall more slowly than generic prices when additional generics enter. Such a possibility is also consistent with some of the empirical works described. To address this issue in detail, we postulate several specifications where one variable captures the overall price decline and a separate variable captures the differential decline in the price of branded products.

The first column in Table 2 is derived from a formal model of spatial competition (see Wiggins and Maness 1998). The specification is very similar to the Cournot analysis. The other specifications relax the highly specific functional form to test the qualitative result that brand-name prices should fall more slowly than generic prices. Column (1) of Table 2 reports the results of the first specification. The control variable coefficients are qualitatively similar to those in section II. The F-statistics and $R^2$ are large. The primary coefficients of interest in column (1) are the coefficient for the inverse of the number of sellers, and the variable interacting this variable with brand name. The inverse of the number of sellers has the incorrect sign but is not statistically significant. In contrast, the results show that generic entry lowers brand-name prices.

The second column in Table 2 reports a logarithmic specification, and the third reports a linear specification. The final column in Table 2 uses HHI in place of a functional form based on the number of competitors. All four specifications show a significant effect of generic entry on brand-name prices but little effect of generic entry on generic prices. The result is that the analysis is that the data indicate faster price declines for brand names than generics, contrary to the conclusions of previous empirical research.

In addition, we examine several nonstructural alternatives. These models also permit empirical examination of how multiple

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
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<tbody>
<tr>
<td>Constant</td>
<td>-77.778</td>
<td>26.731</td>
<td>-39.739</td>
<td>-55.495</td>
</tr>
<tr>
<td></td>
<td>(-9.092)</td>
<td>(2.557)</td>
<td>(-3.985)</td>
<td>(-5.954)</td>
</tr>
<tr>
<td>$f(N_G)$</td>
<td>-18.464</td>
<td>-2.855</td>
<td>-0.433</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(-0.785)</td>
<td>(-1.644)</td>
<td>(-4.313)</td>
<td>-</td>
</tr>
<tr>
<td>HHI</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(5.880)</td>
</tr>
<tr>
<td>Brand-name dummy variable ($BRAND$)</td>
<td>2.962</td>
<td>10.269</td>
<td>8.256</td>
<td>4.720</td>
</tr>
<tr>
<td></td>
<td>(3.870)</td>
<td>(3.643)</td>
<td>(5.999)</td>
<td>(3.451)</td>
</tr>
<tr>
<td>$BRAND \times f(N_G)$</td>
<td>40.379</td>
<td>-2.103</td>
<td>-0.202</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(2.317)</td>
<td>(-2.207)</td>
<td>(-3.391)</td>
<td>-</td>
</tr>
<tr>
<td>$BRAND \times$ HHI</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0002</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-0.708)</td>
</tr>
<tr>
<td>Intravenous products dummy</td>
<td>3.999</td>
<td>5.207</td>
<td>5.922</td>
<td>4.102</td>
</tr>
<tr>
<td></td>
<td>(1.472)</td>
<td>(1.862)</td>
<td>(2.021)</td>
<td>(1.466)</td>
</tr>
<tr>
<td>$F$-statistic</td>
<td>112.32</td>
<td>109.30</td>
<td>110.03</td>
<td>102.34</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.849</td>
<td>0.846</td>
<td>0.847</td>
<td>0.837</td>
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<tr>
<td>Root MSE</td>
<td>0.963</td>
<td>0.956</td>
<td>0.957</td>
<td>0.892</td>
</tr>
</tbody>
</table>

Notes: $N_G =$ number of generic competitors. HHI = Herfindahl index. $t$-statistics are in parentheses. Dependent variable is real price is in 1982–84 dollars. Regressions are weighted OLS. Weights are calculated by number of competitors and in each regression are equal to the standard deviation of the residual for each number of competitors. Fixed effects dummy coefficients are not reported. Regressions only include cases where market has a single brand-name seller and one or more generic sellers. Regressions are based on 565 observations meeting these conditions.
branded sellers affect prices, in addition to the impact of generics on branded prices, and vice versa.

Frank and Salkever (1992) developed a model for a “segmented market” in pharmaceuticals with two groups, a loyal group of price-inelastic brand-name consumers and a relatively price sensitive group of consumers. They argue there is little competition between these segments. In such a case, the prices of brand-name products will be unaffected by the number of generic competitors and, symmetrically, the number of brand-name sellers ought not affect generic prices. An alternative view is that all products besides the original pioneer are generic. This view is implicit in much of the empirical literature, which generally examines only the pioneer’s prices, implicitly treating all entry as generic. This approach implies that pioneer products represent one category and all other products represent another.

Our approach, in contrast, separates products sold by other innovative companies, because these companies are the ones who sell the incremental “branded” products (so-called branded generics) in the sample. To the extent that branded entry causes larger price effects, the results indicate that branding leads to more effective price competition by incrementally reducing prices in the branded and/or generic segments.

Table 3 presents weighted least squares regressions investigating these hypotheses. A pooling test was conducted to see if the three product categories could be pooled with respect to the effect of the number of sellers, and the results reject pooling. Subsequent pooling tests were conducted for pooling pioneers and other brand names and for generics and brand names, and in each case pooling was rejected. Accordingly the econometric results will analyze the separate effects of branded and generic entry.

Table 3 presents weighted least squares models of product differentiation:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pioneer Products Only</th>
<th>Brand-Name (Other than Pioneer)</th>
<th>Generic Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>21.601</td>
<td>42.207</td>
<td>13.516</td>
</tr>
<tr>
<td></td>
<td>(7.599)</td>
<td>(4.965)</td>
<td>(6.736)</td>
</tr>
<tr>
<td>$1/(N_G + 1)$</td>
<td>14.183</td>
<td>5.106</td>
<td>0.411</td>
</tr>
<tr>
<td></td>
<td>(4.270)</td>
<td>(1.431)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>$1/(N_B + 1)$</td>
<td>−8.417</td>
<td>−57.222</td>
<td>0.279</td>
</tr>
<tr>
<td></td>
<td>(−3.173)</td>
<td>(−2.904)</td>
<td>(0.206)</td>
</tr>
<tr>
<td>$N_G$</td>
<td>−0.085</td>
<td>−0.094</td>
<td>−0.155</td>
</tr>
<tr>
<td></td>
<td>(−2.409)</td>
<td>(−3.087)</td>
<td>(−7.551)</td>
</tr>
<tr>
<td>$N_B$</td>
<td>−2.628</td>
<td>−5.091</td>
<td>−0.882</td>
</tr>
<tr>
<td></td>
<td>(−4.077)</td>
<td>(−4.395)</td>
<td>(−2.364)</td>
</tr>
<tr>
<td>Intravenous products dummy</td>
<td>20.531</td>
<td>13.892</td>
<td>3.535</td>
</tr>
<tr>
<td></td>
<td>(10.378)</td>
<td>(19.502)</td>
<td>(2.544)</td>
</tr>
<tr>
<td>Mean of price (weighted)</td>
<td>36.72</td>
<td>12.58</td>
<td>5.93</td>
</tr>
<tr>
<td></td>
<td>(1.97)</td>
<td>(2.51)</td>
<td>(1.41)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>394</td>
<td>171</td>
<td>2491</td>
</tr>
<tr>
<td>$F$-statistic</td>
<td>214.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
<td>0.830</td>
</tr>
</tbody>
</table>

Notes: Dependent variable = price. $N_G$ = number of generic competitors. $N_B$ = number of brand-name competitors. $t$-statistics are in parentheses. Dependent variable is real price is in 1982–84 dollars.

28. See also Grabowski and Vernon (1992). Frank and Salkever (1997) provide empirical support for the segmented market hypothesis by demonstrating that branded prices tend to rise with generic entry while generic prices tend to fall.
29. See, for example, Grabowski and Vernon (1992), Caves et al. (1991), and Frank and Salkever (1997).
30. Due to data limitations, the unreported fixed effects discussed earlier are pooled across all three types, pioneer, other brand name, and generic. To the extent that these fixed effects represent cost and demand differences among chemicals, this specification is correct.
prices, but the coefficient on brand-name products is about ten times as large as the coefficient on generic products and is the incorrect sign. Nevertheless, the results show significant competition between these product groups, which is inconsistent with the segmented market hypothesis and with the notion that all sellers other than the pioneer should be treated similarly.

Turning to the generic price equation, the results clearly indicate that generic firms do respond to brand-name entry. Note, however, there are important differences in how generic prices respond to other generic as opposed to brand-name entry. The linear term for generic entry is large and significant, whereas the inverse term is small and not significant. For brand-name entry the response is similar, but the effect of brand-name entry on generic prices is substantially larger (−0.88 per brand-name entrant versus −0.16 for an additional generic entrant). The results once again show significant competition between branded products sold by innovators and generics.

The results for pioneer products—products sold by the original developer—also contrast with the segmented market hypothesis. Generic entry has a large and statistically significant effect on pioneer prices, both for the linear and nonlinear terms. Hence pioneer products do indeed lower prices quite significantly in the face of additional generic competition.31 Furthermore, there is suggestive support for the hypothesis that branded entry also affects pioneer prices in that the linear term is quite large and statistically significant, although the inverse of the number of brand-name sellers has the wrong sign.

Hence the results support the argument that there is significant competitive interaction between pioneer, brand name, and generic firms. These results indicate considerable competition and show that increases in the number of sellers in any segment generally reduce prices in the remaining segments. This competition suggests that markets are less segmented than previous discussions suggest.

### IV. CONCLUSIONS

This article has provided an empirical investigation of the relationship between price and the number of sellers in pharmaceuticals. The analysis used a data set covering all anti-infective products and showed that initial entry led to sharp price reductions, with prices falling from the range of more than $60 per prescription for single sellers, $30 when there are two or three sellers, and less than $20 when there are four or more sellers. The results also show that prices continued to decline with additional entry, eventually approaching $4 for products with more than 40 sellers.

The results show that increases in the number of competitors significantly reduce prices, even when there are numerous sellers. These results tie in nicely with those of Bresnahan and Reiss (1991). Using small, isolated county seats, they find that the competitive effects of entry diminish after the third or fourth entrant but that prices stabilize above those in unconcentrated urban markets. The results here show a similar, rapid initial price decline, and then go on to show a continuing steady decline as the number of sellers rises from a few to many.

The analysis also showed, however, that existing models do not explain well the observed pricing pattern. The analysis showed prices broadly consistent with Cournot quantity setting, though prices declined more with large N than that model would predict.

The analysis also ties into the emerging work on pharmaceutical prices. The analysis here has extended that work in several directions. One direction is to provide a much more comprehensive analysis of pricing in a specific, important therapeutic category. Our results show substantial price sensitivity and stand in contrast to results found by Caves et al. and Grabowski and Vernon. There are several possible reasons for these differences. One is that the analysis here relied on all anti-infectives, not restricting attention to the period closely following patent expiration. The greater variation in the number of sellers also provides a richer data set particularly because the analysis used data exclusively since 1984, when there were large numbers of generic sellers. This date is important because it follows the Waxman-Hatch Act, which eased the burdens of generic entry. A second possible reason is that anti-infectives may be more price-sensitive than other segments of the pharmaceutical

31. There are several possible reasons for these differences from Grabowski and Vernon. Perhaps the most important is that we have a much larger sample—they considered only 18 products. It is also possible that their results are confounded due to difficult to control for cost differences, or that our results are special due to the differential characteristics of anti-infectives.
industry. This possibility, of course, means that one must be careful in drawing inferences from this analysis to pharmaceuticals more generally.  

The analysis also provided an econometric investigation of differentiated product models by treating brand-name and generic products as differentiated. The problem is to explain the persistent price difference between brand-name products and their generic competitors. The results indicate that a general spatial model of product differentiation does not adequately explain pricing behavior in the pharmaceutical industry because brand-name products respond aggressively to generic entry. The results, however, also reject the segmented market hypothesis, showing instead that there is important competition between the pioneer, brand name, and generic segments. Multiple products achieve brand recognition, and there are important differences in the competitive effects of additional branded entry compared to the effects of incremental generic entry. For both generic and brand-name firms, there is a significant inverse relationship between price and the number of competitors, whether those competitors are brand name or generic producers.

The broad implication of the analysis is that entry of additional sellers reduces prices much more substantially than previous work would suggest. The extent to which these results carry over to other therapeutic classes remains an important, unresolved issue.

REFERENCES


32. Reasons for such caution include possible cost and regulatory differences, the fact that a single prescription is often part of a maintenance program of therapy in other pharmaceutical areas, and such repeated use may lead to differences in brand loyalty and competition.


