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Characteristics of demand for pharmaceutical products: an examination of four cephalosporins

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We model demand for four cephalosporins and compute own- and cross-price elasticities between branded and generic versions of the four drugs. We model demand as a multistage budgeting problem, and we argue that such a model is appropriate to the multistage nature of the purchase of pharmaceutical products, in particular the prescribing and dispensing stages. We find quite high elasticities between generic substitutes and also significant elasticities between some therapeutic substitutes.

1. Introduction

■ The pharmaceutical industry has always been of interest to economists as a large and internationally competitive industry. Recently it has come under policy scrutiny as a component of a much-debated health care system, with proposals ranging from preserving the current status of the industry to full price controls on pharmaceuticals. To understand the implications of various proposals, it is important first to understand the market environment in which the industry operates; of particular interest is the degree of price sensitivity. To study this issue we focus on a particular segment of the market for pharmaceuticals, cephalosporins, a type of antiinfective drug, during the late 1980s. We look at four particular compounds that are close therapeutic substitutes, i.e., they can be prescribed for many of the same

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conditions. Three of these drugs lost patent protection and experienced generic entry during the period in which we study them. Thus we are able to observe patterns of substitution between branded and generic versions of the same drug (generic substitutes) in addition to those among similar drugs (therapeutic substitutes).[1]

Although the practical and policy motivations for studying the pharmaceutical industry are strong, the structure of demand for pharmaceuticals also holds great interest for the academic researcher. Pharmaceuticals are unusual in that the consumer of the product is typically not the one deciding which product to consume and often not the one paying for the product. This situation contrasts with the standard consumer paradigm in economic modelling—a single consumer under full information maximizes a utility function subject to a budget constraint—and raises interesting agency and informational issues. We shall now discuss the typical process of prescribing and dispensing prescription pharmaceuticals to highlight some of the more interesting academic issues, but also to inform our modelling strategy and our interpretation of the results.

The process is begun, of course, when a physician writes a prescription for a drug. By "drug" we mean chemical entity, but the prescription will include information such as form, dosage, frequency, and so forth. The prescription may be written for the generic name of the drug or for any brand name under which the drug is sold. Depending on the therapeutic class, physicians may have quite a bit of scope in the drug they choose to prescribe for a given condition.[2]

Over the years, researchers have found direct evidence that physicians' informational limitations about relative prices of drugs might be important (e.g., Steele, 1962; Walker, 1971; and Temin, 1980). Anecdotal evidence also supports this belief. The standard references on pharmaceuticals, *Physicians' Desk Reference* and *Drug Facts and Comparisons,* have incomplete or no information about relative prices across drugs.

Although changes in the last few years in the market for pharmaceuticals will not be directly relevant to the results in this article, it is worth mentioning that anecdotal evidence suggests that physicians are becoming better aware of relative prices. First, Medco, a managed care drug company, is reported to persuade 25% to 50% of the physicians it contacts to switch (Boston Consulting Group, 1993).[3] Also, Hellerstein (1994, p. 3) finds that the "physicians who treat many patients who belong to an HMO or other Pre-Paid Plan prescribe generics more frequently to *all* their patients" (emphasis added). These findings suggest that physicians contacted by managed care drug companies or affiliated with HMOs have a greater awareness of relative prices. As more physicians are joining these ranks (*New York Times,* 1994; Boston Consulting Group, 1993), the state of knowledge of physicians about prices should continue to improve, on average. Finally, pharmaceutical marketing aimed at physicians is becoming a source of information on prices of some drugs, in sharp contrast to pharmaceutical marketing of the past.[4]

[1] Several studies focus more directly on issues surrounding generic entry in pharmaceuticals, such as determinants of entry, strategic pricing at the time of entry, changes in demand induced by entry, and so forth. See Caves, Whinston, and Hurwitz (1991), Frank and Salkever (1992, 1995), Grabowski and Vernon (1992), Scott Morton (1995), Stern (1996), and Wiggins and Maness (1995).

[2] For example, several chemically distinct but similarly working H2 antagonists are available for the treatment of duodenal ulcers. Similarly, several ACE inhibitors are used in the treatment of hypertension. Also, many types of bacterial infections are susceptible to numerous chemically distinct antibiotics. (See *Drug Facts and Comparisons.*)

[3] Managed care drug companies simply contact physicians on the phone and inform them of price and characteristic differences, trying to persuade them to switch prescriptions. They have no authority over the physicians, so it would be difficult to attribute change in behavior to something other than an informational effect.

[4] Advertising for ACE inhibitors is an example. In their marketing campaigns targeted at physicians,

Incentives to and constraints on physicians' writing of prescriptions are supplied by managed care programs to which the physician belongs as well as formulary lists and rules of other organizations. Another possible (but surely less important) source of incentives is a price-sensitive patient's threat to switch to a physician who prescribes lower-cost pharmaceuticals. For the purposes of our study, estimating a demand system for a period before the most significant managed care penetration, it is possible that whatever incentives and constraints a physician encounters in prescription writing are not strong. Although later in this article we shall estimate models that allow us to directly observe price sensitivity, we have identified potential reasons why the degree of price sensitivity might be less than optimal (i.e., less than a fully informed single agent might have).

The second stage in the process is the dispensing of the product. Just as the physician often has choice in prescription writing, there is often some scope for choice in what product to dispense, typically only in the case of "multisource" drugs, i.e., drugs that have lost patent protection and thus are supplied by a number of manufacturers.[5] As of 1989, all states had laws that at least allow pharmacists to substitute cheaper generic versions when dispensing, assuming the physician does not explicitly prohibit such substitution on the prescription. Again, analogous questions arise at this second stage of the process: Are dispensing pharmacists aware of relative prices, and under what incentives and constraints do they operate in choosing what product to dispense? First, it is clear that for the most part, a dispensing pharmacist is aware of relative prices. Second, in addressing the question of incentives and constraints, we note that pharmacies have higher relative markups on generics and will often have an incentive to dispense the cheaper generic version (Grabowski and Vernon, 1992). Constraints on their behavior include state mandatory substitution laws[6] and rules and constraints placed on pharmacists who are affiliated with or being reimbursed by insurance companies, HMOs, government agencies, or other organizations. In sum, these potential information and agency problems seem more serious at the first stage of the pharmaceutical buying process, the prescription stage, than at the second stage, the dispensing stage.

We model the demand for these drugs as a two-stage budgeting problem. Using data on prices and quantities of the various drugs, we estimate this decision tree, or demand system. We think that the approach of multistage budgeting is particularly appropriate for modelling the demand for pharmaceuticals, due to the multistage nature of the process itself. The stages we use correspond roughly to the different decision makers in the process of choosing a pharmaceutical product, as discussed above. First, the prescribing physician chooses the chemical compound. Second, the pharmacist dispenses the branded or generic version of that particular drug, sometimes in conjunction with the patient and often constrained by laws, insurance company policies, or both. Modelling this process by multiple stages allows us to isolate and focus on one stage or the other, thereby gaining clues to the behavior of the two different groups of decision makers. We can also estimate the matrix of cross-price elasticities for the pharmaceutical products in both their branded and generic forms. Upon estimation of the demand system, we find evidence of substantial price

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Parke Davis offers a "single agent guarantee" on Accupril, a pledge to pay for any other hypertension medications a patient needs to take, and Ciba Geigy offers a "lifetime price guarantee" on Lotensin, a promise to rebate any subsequent price increases to the payor.

[5] All of these products would be certified by the U.S. Food and Drug Administration (FDA) to have chemically identical active ingredients and to be "bioequivalent," so-called generic versions of the drug.

[6] Twelve states *require* substitution of a cheaper generic version unless explicitly prohibited by the physician, according to the Pharmaceutical Manufacturers Association.

sensitivity in the choice between generic substitutes and less evidence of price sensitivity in the choice among therapeutic substitutes. This basic result is borne out in subsequent elasticity estimates: high cross-price elasticities between generic substitutes and lower, often insignificant, cross-price elasticities between pairs of therapeutic substitutes.

The structure of the article is as follows. In Section 2 we introduce the model of demand. In Section 3 we describe the four drugs we study and our dataset on them. In Section 4 we discuss the empirical implementation of the model and estimation techniques and the results from our base model and variations on it, as well as the computation of a therapeutic group price index based on our demand system estimates. We conclude in Section 5.

2. The model

■ The models of demand we use are variants of a model of multistage budgeting due to Gorman (1971). (See Hausman, Leonard, and Zona (1994) and Hausman, Leonard, and McFadden (1995) for examples of empirical implementation of these models.) Commodities can be partitioned into groups so that a choice within a group is made conditional on choice of that group. We essentially construct a tree to represent the structure of choice, where the bottom level of the (inverted) tree has a node for each commodity, and each level of the tree represents an ever-coarser partition of the commodities. Conceptually, a consumer moves down the tree toward an eventual purchase by considering the attributes of the commodities that could be reached by each branch and a price index of the commodities of each branch. Whereas such structure is often placed on the pattern of cross-price elasticities in a system in order to be able to estimate them, we think that imposing this structure is easy to justify because each stage corresponds, at least roughly, to the different sets of decision makers. Also, normal concerns about the utility consistency of a demand system are of less importance in our empirical setting, owing to the different agents operating.[7]

The natural grouping of technologically similar products in this empirical setting is an argument for our approach over, say, a nested logit model—our set of constraints allows free estimation of elasticities between every pair of products in a group and between every product and every other group. In addition, an important theoretical advantage of a nested logit, aggregability, seems less important in an empirical setting with a multitude of purchasing agents such as ours. Finally, although a discrete-choice model has an advantage over ours in accommodating new goods at upper levels of the tree, that advantage is not crucial in our setting because we see no entry above the branded/generic level during our time period. See Stern (1996) for an interesting application of the nested logit methodology to pharmaceutical products and a discussion of its advantages, and see Anderson, de Palma, and Thisse (1992) for a general discussion of such models.

Figure 1 shows the structure of the tree for our specific case.

The model we use has two levels,[8] the top level representing demand for the four drugs of interest separately and the bottom level representing demand for the generic or branded versions of each drug. A "group" in the more general discussion

[7] One could perform a direct test of agency in this market by testing parameter restrictions implied by utility theory; however, since these restrictions are often rejected in empirical work where no agency issues exist, the value of such a test is questionable.

[8] In the estimation section we mention one specification with an extra equation on top for the demand of the four cephalosporins relative to the demand for penicillin and other cephalosporins.

is, therefore, a "drug" here, and group members would be the branded and generic versions of that drug.

We model the choices at both levels similarly to Hausman, Leonard, and Zona (1994). We begin at the bottom level. We describe the consumer's choice between a branded and generic version with the following equation:

$$\text{bottom:} \quad s_{D0} = \alpha_{0D} + \beta_D \log(r_D/p_D) + \gamma_{D0}\log(p_{D0}) + \gamma_{D1}\log(p_{D1}).$$

The left side of each equation, s_{D0}, is the revenue share of the branded version of drug D (D = 1 (cephalexin), 2 (cefadroxil), 3 (cephradine)). The right-side variables are r_D/p_D, the revenue of drug D over the weighted price of drug D, and p_{D0} and p_{D1}, the prices of the branded and generic versions of drug D. We think of r_D/p_D as playing the role of quantity. It is the dependant variable in the top level. We do not have a share equation for the cefaclor group, of course, because branded share $\equiv$ 1. This equation is essentially the Almost Ideal Demand System of Deaton and Muellbauer (1980). Also, it is natural to constrain $\gamma_{Db} = -\gamma_{Dg}$, thus making the assumption that consumers care only about the *relative* prices of branded and generic versions once they have decided on a particular drug.

We can calculate conditional elasticities, i.e., elasticities conditional on expenditure on a particular drug, using only parameters and variable values from these equations. We differentiate, holding r_D constant, and obtain the conditional elasticity of the branded version.

$$e^D_{[D0]j} = \frac{\partial \log q_{D0}}{\partial \log p_{Dm_j}} = \frac{1}{s_{D0}}\left\{-\beta_D \frac{\partial \log p_D}{\partial \log p_{Dm_j}} + \gamma_{Dm_j}\right\} - 1_{[m_j=0]}.$$

The expression for the generic version is similar. Note that this conditional elasticity is only defined for products in the same group, here just denoted group D. Here we use 1[·] for the indicator function for condition [·]. We use a Stone weighted price, $\log p_D = \Sigma_i s_i \log p_i$, where s_i is the revenue share of the drug within group D; therefore, $\partial \log p_D/\partial \log p_{Dm_j} = s_{Dm_j}$.

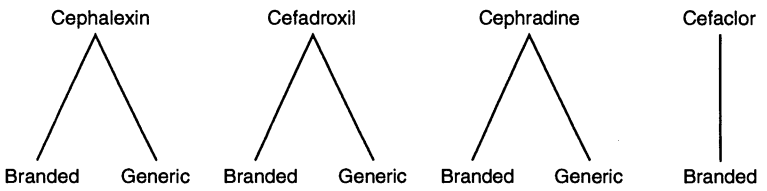
For the top level we describe a consumer's choice among the four drugs:

$$\text{top:} \ \log(q_D) = \eta_D + \xi_D \log(R) + \delta_{D,1}\log(p_1) + \delta_{D,2}\log(p_2) + \delta_{D,3}\log(p_3) + \delta_{D,4}\log(p_4).$$

The left side of each equation (we have four equations) is the log of the quantity of drug D. The right side has the logs of R, total revenue for all cephalosporins, and p_D, D = 1, 2, 3, 4, weighted prices of the four drugs. The quantity consumed of each drug, then, is described as a function of the total revenue and the weighted prices of each of the four drugs. Note that our specification does not impose adding

FIGURE 1

THE FOUR CEPHALOSPORINS



up at the top level because the revenue measure is total revenue for all cephalosporins.

We can also compute "unconditional" elasticities (elasticities conditional on total expenditure on cephalosporins). We substitute the top-level equation into the bottom-level equation for $\log(r_D/p_D) = \log(q_D)$ and differentiate. We obtain

$$e_{[D0]j} = \frac{\partial \log q_{D0}}{\partial \log p_{D_j m_j}}$$

$$= \frac{\beta_D \delta_{D,D_j} \dfrac{\partial \log(p_{D_j})}{\partial \log(p_{D_j m_j})} + \gamma_{D0} 1_{[D_j=D]}}{\alpha_D + \beta_D\left(\sum_{k=1}^{4} \delta_{D,k} \log(p_k) + \xi_D \log(R) + \eta_D\right) + \gamma_{D0}\log(p_{D0}) + \gamma_{D1}\log(p_{D1}) + \dfrac{\partial \log(r_D)}{\partial \log(p_{D_j m_j})} - 1_{[D_j=D, m_j=0]}}.$$

Using the chain rule and properties of the Stone weighted price, we then calculate

$$e_{[D0]j} = \frac{1}{s_{D0}}\{\beta_D \delta_{D,D_j} s_{D_j m_j} + \gamma_{Dm_j} 1_{[D_j=D]}\} + s_{D_j m_j} 1_{[D_j=D]} + \delta_{D,D_j} s_{D_j m_j} - 1_{[D_j=D, m_j=0]}.$$

These elasticities are defined for all pairs of products.

3. The four drugs and our data

■ In January 1971 Eli Lilly introduced Keflex, generic name cephalexin, the first of a new class of antiinfective drugs called cephalosporins.[9] Cephalexin was an important medical advance for two main reasons: it was active against some previously untreatable bacterial infections, and it caused allergic reactions in many fewer patients than penicillins did. Many similar cephalosporins followed. Bristol Myers Squibb introduced Duricef and Ultracef, generic name cefadroxil, and, in a joint marketing agreement, Bristol Myers Squibb and Smith Kline Beecham introduced Velosef and Anspor, respectively, generic name cephradine. These three drugs were followed by several other minor drugs, together making up the class of "first-generation cephalosporins." Eli Lilly later introduced Ceclor, generic name cefaclor, purported to be a therapeutic innovation over the first-generation cephalosporins. It was the first "second-generation cephalosporin." These four distinct drugs, or chemical entities, cephalexin, cefadroxil, cephradine, and cefaclor, are the focus of the article.

A number of characteristics of these drugs suggest that the four, or at least three, are close substitutes in a technological sense. The first three molecules are very similar in chemical structure. Cefaclor's chemical structure is less similar to the other three than they are to each other, and chemical structure may be a proxy for unmeasured attributes. All four drugs are active against much the same types of organisms (see Table 1). Table 2 lists approved indications, i.e., disease states or conditions for which the FDA has approved use of a drug.[10] While there is less overlap than in Table 1, it should be noted that drugs can be, and often are, prescribed for conditions other than their labelled indications. Finally, all four drugs are sold primarily in oral dosage forms,

[9] Antibiotic activity was first observed in isolates from shellfish from the Greek island of Cephalos.

[10] The information for both Tables 1 and 2 comes from *Drug Facts and Comparisons.*

TABLE 1 Susceptible Organisms

	Cephalexin (Keflex)	Cefadroxil (Duricef, Ultracef)	Cephradine (Velosef, Anspor)	Cefaclor (Ceclor)
Staphylococci	*	*	*	*
Streptococci, beta-hemolytic	*	*	*	*
Streptococcus pneumoniae	*	*	*	*
Escherichia coli	*	*	*	*
Hemophilus influenzae	*		*	*
Klebsiella sp	*	*	*	*
Moraxella catarrhalis	†			*
Neisseria gonorrhoeae				†
Proteus mirabilis	*	*	*	*
Bacteroides sp				*
Peptococcus sp				†
Peptostreptococcus sp				†

* Generally susceptible, † Demonstrated in-vitro activity.

an important clinical consideration. In contrast, many other cephalosporins are, for the most part, administered intravenously, in a rather different clinical setting.

We chose to examine this group of drugs for several reasons. First, we can study therapeutic substitution in this setting due to the similarities among these drugs. Second, three of the compounds lost patent protection[11] within a 26-month period and experienced significant generic entry: cephradine in January 1987, cephalexin in April 1987, and cefadroxil in March 1989. This significant generic entry allows us to study generic substitution in this setting. Third, these are widely prescribed drugs, and they constitute a substantial segment of the pharmaceutical market. Over the period October 1985 to December 1991, total wholesale sales to drugstores and hospitals in the United States of the four drugs was $2,529,000,000.

Finally, we should mention that the generic entrants for the drug cefadroxil experienced some legal problems during the period of time of our data. The incumbent argued that generic entrants had infringed upon a relevant patent, and the entrants eventually had to withdraw their products (after our data period). This pending litigation quite possibly affected consumer choices between the branded and generic versions of the drug—drugstores might not have wanted to buy and stock large quantities of a drug that they would then be prevented from selling. This effect could be exacerbated by the fact that our data are at the wholesale level.

The data for this project come initially from IMS America, a firm that does marketing research for the pharmaceutical industry.[12] Merck Pharmaceuticals was also helpful in allowing us access to its library of IMS data. We have data on all antiinfective drugs, but we will be concentrating attention on the four previously mentioned. The data are in the form of a monthly time series from October 1985 to March 1991 of quantity and revenue of wholesale sales at the level of manufacturer/drug presentation,[13]

[11] We use the term "patent protection" somewhat loosely here as any type of protection that would have precluded generic entry until a specific date. The exclusive right to sell the drug in the United States enjoyed by the incumbent could be the result of the FDA withholding or delaying Abbreviated New Drug Application (ANDA) approval to new manufacturers, for instance, rather than the normal protection from entry conferred by a patent.

[12] This dataset is similar to the one used in Griliches and Cockburn (1994), and much of the groundwork they established in constructing that dataset was useful to us.

[13] A presentation is a particular choice of packaging and doseform for a product, for example, 150-milligram coated tablets in bottles of 100, or 25 milliliters of 5% aqueous solution in a vial for intravenous injection. A drug will often be sold in many presentations simultaneously.

TABLE 2 Indications

	Cephalexin (Keflex)	Cefadroxil (Duricef, Ultracef)	Cephradine (Velosef, Anspor)	Cefaclor (Ceclor)
Lower respiratory tract infections	*		*	*
Upper respiratory tract infections	*	*	*	*
Otitis media	*		*	*
Skin infections	*	*	*	*
Urinary tract infections		*	*	*
Bone infections	*			
GU infections	*			
Perioperative prophylaxis			*	

separated by hospital and drugstore sales. The IMS information on presentation was coded to allow consistent comparison across drugs, manufacturers, and presentations, using *Drug Facts and Comparisons* and *Physicians' Desk Reference.* Of the total sales over our data period for the four drugs we study, 93% was sold to drugstores and 7% to hospitals. See Table 3 for the respective revenue shares of these three drugs in the drugstore, hospital, and total markets.

The model is estimated using derivative, or aggregate, data of these data. For example, for cephalexin, the branded manufacturer sold 29 different presentations, and there were 341 different generic[14] manufacturer/presentation combinations. (It is sometimes difficult to identify particular generic manufacturers, so we will stick with this cruder count of combinations.) The branded manufacturers sold 30 presentations each of cefadroxil and cephradine, and there were 78 and 97 different generic manufacturer/presentation combinations, respectively. The branded manufacturer sold 16 presentations of cefaclor. The derivative data are obtained by first classifying each record three ways: as drugstore or hospital sales, by drug, and as branded or generic manufacturer, thus producing fourteen classes. We then aggregate monthly revenues by class and compute Divisia price indices by class.[15] Note that presentations are linked in at one so that these price indices reflect only price *changes* in existing presentations within each class. The seven "products" we obtain are then cephalexin, cefadroxil, and cephradine, all three in branded and generic versions, and branded cefaclor. We have each of these products in both markets, hospitals and drugstores. We then link the price indices for the four (or two) classes within each drug using weighted price ratios of common presentations in the first or entering month. (The Stone weighted price that appears in the top level of our demand system will, therefore, reflect a large price decrease when generics enter.) Finally, all price and revenue series are deflated by the medical care CPI. Figures 2, 4, 6, and 8 show all fourteen of these price indices.[16]

[14] We use the term "branded manufacturer" as a synonym for incumbent, or holder of exclusivity or patent rights, and "generic manufacturer" as a synonym for entrant. Some "generic manufacturers" are actually large drug companies with well-known names.

[15] We aggregate over presentation for two reasons. First, the large number of presentations of each drug that come into and out of the market would pose serious computational problems. Second and more important, we want to abstract away from the less economically interesting issue of choice of presentation.

[16] Figure 6, Cephradine Prices, reflects a strange two-month spike in prices near the beginning of our data period. Although we are not sure of the cause of the spike, we believe it was an actual price increase rather than a mistake in the data: it appears in several presentations of the drug and lasts for two months instead of just one.

TABLE 3 Revenue Shares

	Drugstore	Hospital	Total
Cephalexin	28%	2%	30%
Cefadroxil	14%	1%	15%
Cephradine	3%	1%	4%
Cefaclor	48%	3%	51%
Total	93%	7%	100%

Figures 3, 5, 7, and 9 show all fourteen revenue series.[17] Finally, we compute a quantity index by dividing revenue by the price index for each of the fourteen series. Other methods of aggregation over presentations were available to us.[18] Note, however, that since aggregation is done within a drug, quantity never has to be compared between drugs.

It should be noted that an implicit assumption in the creation of this dataset is that generic manufacturers are equivalent, or that their products are perfect substitutes. This assumption could be problematic in some classes of drugs. For instance, in drugs used for chronic conditions, patients often form loyalties to one particular generic because of tablet shape or color, perhaps. In addition, some "generic" manufacturers try to induce product differentiation by promoting their own brand names, such as the names Nuprin and Advil being given to generic Motrin, ibuprofen. Neither situation occurs with our set of drugs, so we feel more justified in our assumption. Also, it should be noted that our revenues and prices are wholesale measures. Unfortunately, retail revenues and prices were not available to us. We are primarily interested in the general pattern of elasticities, though, and the pattern we estimate from the wholesale data should be fairly robust to reasonable markup policies. Finally, we should point out that while IMS gathers data on detailing and other advertising in the pharmaceutical industry, we do not have those data for the drugs we study here.

4. Estimation and results

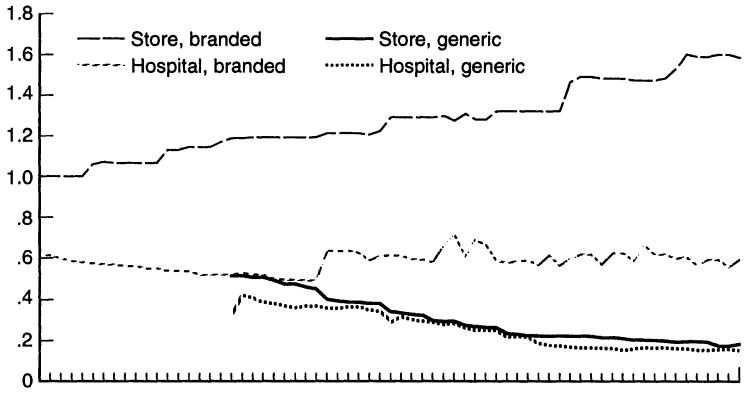
■ **Estimation.** In discussing the empirical implementation of the model presented in Section 3, two main issues arise, what econometric techniques to use in estimating the system and which, if any, instruments to use at each level of the system. First note that the basic equations we will be estimating are those of the model presented earlier with additive errors. We use the data discussed in Section 3, essentially monthly time series of price and revenue for the seven drug products, by drugstore and hospital sales separately. We add additional explanatory variables in certain specifications, which we discuss later. We estimate the model both equation by equation (using ordinary least squares or two-stage least squares) and as a system (using seemingly unrelated regressions or seemingly unrelated regressions with instrumental variables). Note that the equations will not, in general, have the same number of observations, due to generic entry during our data period. We therefore estimate the bottom-level equations, the branded budget share equations for each drug, using only data after generic entry for

[17] Note that Figure 9, Cefaclor Revenues, exhibits pronounced seasonality in drugstore revenues, in contrast to the other drugs. This is evidence that cefaclor might not be a close therapeutic substitute to the other three.

[18] We could have computed quantity by adding up doses or milligrams of active ingredient, say, for each presentation. A dose, however, is not a well-defined object—different doses could be recommended for different indications—and certain presentations are used disproportionately for certain indications. Number of milligrams of active ingredient is problematic for similar reasons.

FIGURE 2

CEPHALEXIN PRICES



each drug, but estimate top-level equations, the quantity equations for each drug, using data for the whole period. The top-level estimates, then, reflect the reactions to generic entry in each of the drugs.

Another issue is the treatment of endogenously determined variables. In particular, we would like to find supply-shifting instruments for endogenous prices in order to identify demand. The first question is which prices, if any, are endogenous. If the prices for individual drugs are predetermined and hard to change,[19] the necessity of instrumenting is lessened. It is also possible that the nature of competition might give us some insight into the question of identification. If, for instance, a generic fringe with two or more firms is perfectly competitive and has constant returns to scale in the region in which they are producing, then generic prices, at least, are not endogenous and no instrument is necessary. These arguments assume consistent pricing strategies, an assumption perhaps more palatable for our relatively short time series and during a period before managed care effected important changes.

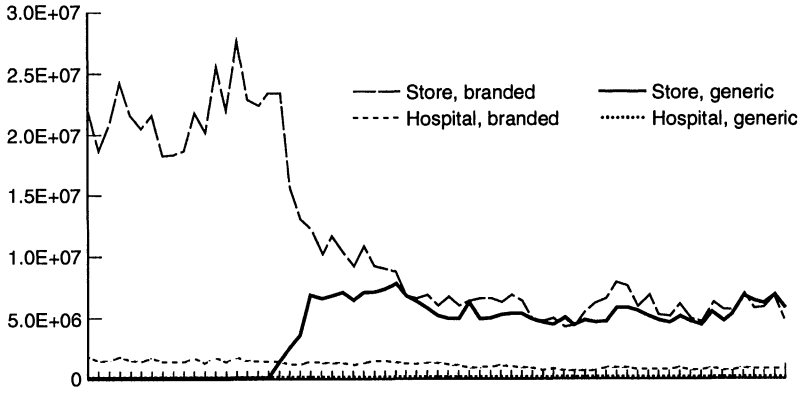
Not being willing to assume exogeneity *ex ante,* we turn to the issue of suitable instruments. Typical cost-shifting instruments are unavailable at the level of individual drug. One possibility is exploiting a changing competitive environment to identify demand. The idea is that if demand is fairly stable over time but prices are changing due to different strategic responses by the firms in the market, we should be able to trace out demand curves. Following Stern (1996) and Feenstra (1995), the number of firms in the market could be such an indicator of a changing competitive environment.[20] The power of the instrument depends on the equilibrium being a function of the number of firms. A competitive fringe, mentioned above, would be an example where this instrument would have little or no power. The validity of the instrument depends on demand not shifting either as the result of or the cause of a changing competitive environment, and in general it might be suspect. For instance, firms could be entering or exiting a market in response to changing demand characteristics. Such a concern might be relatively less important in new markets created by patent expiration. New

[19] We feel somewhat justified in this belief by inspection of the branded price series, fairly constant with regular and regularly spaced price increases. While these branded price movements are not inconsistent with short-run strategic behavior, some of the series very much resemble a predetermined pricing strategy.

[20] Actually, we use the number of different presentations produced by different manufacturers because linking up generic manufacturers across presentations is not always possible in our dataset. This variable would also be an indicator of competitive environment, using the reasoning above.

FIGURE 3

CEPHALEXIN REVENUES



generic firms could simply be entering over time exogenously because they have different lead times to start manufacturing a new product.

Finally, one possible source of instruments is the drugstore/hospital split in the data. The two markets are almost entirely independent in the sense that it would be difficult for a consumer to substitute between them. Also, the two markets would experience the same manufacturing cost shocks to a great extent, if any existed or were important. It might be possible, therefore, to use hospital prices as instruments for drugstore prices. The two markets could also experience the same demand shocks, though, such as an epidemic of ear infections or favorable news about the efficacy of the drug, thus making the instruments invalid. We touch on this problem in the next subsection. This approach is similar in flavor to Hausman, Leonard, and Zona (1994), who use prices in different cities as instruments for each other.

□ **Base model.** In this subsection we discuss in detail one specification, which we call our base model, and the estimation results from it. We focus on two of the four drugs, cephalexin (drug 1) and cephradine (drug 3), in the drugstore market for our base model. We choose to look initially at just drugs 1 and 3 because cefadroxil (drug 2) was involved in legal battles and cefaclor (drug 4) does not seem to be as close a

FIGURE 4

CEFADROXIL PRICES

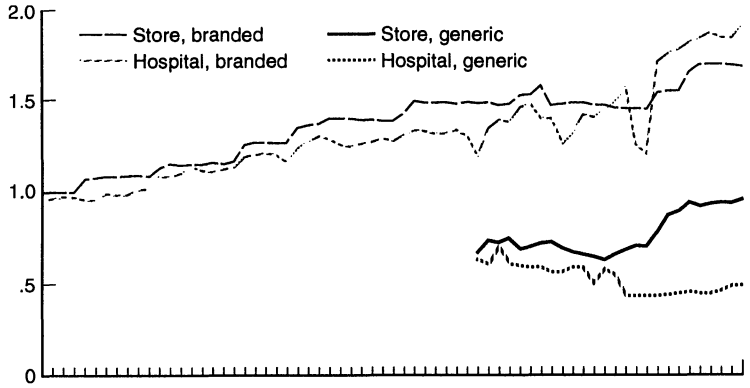
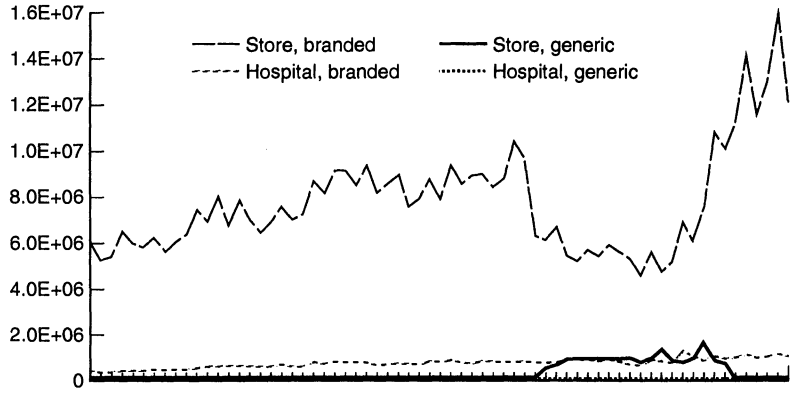


FIGURE 5

CEFADROXIL REVENUES



substitute, based on therapeutic considerations. We focus on the drugstore market because it is a much larger and more important market for these drugs, and the procedure for prescribing and dispensing drugs that we describe in the introduction and model is more closely approximated in the drugstore market than in the hospital market. We consider additions to this base model in a subsequent section.

We estimate the top level, demand for each of the drugs, and the bottom level, revenue shares of the branded versions, first by SUR, not using any instruments. See Tables 4 and 5 for specifications and estimates. Note that season dummies S have been added at both levels and a time trend t has been added in the top level. Also, the coefficients on $\log(p_{D0})$ and $\log(p_{D1})$ are constrained to add to zero. In the top-level estimation, note that both the group own- and cross-price elasticities for drug 3, the coefficients on $\log(p_1)$ and $\log(p_3)$ in the second equation, are significant and the expected sign. In contrast, neither of the group elasticities for drug 1 is significant and both are the wrong sign.

As we mentioned in the data section, the branded and generic price series were linked using price ratios of common presentations in the entering month. That method of linking results in the Stone weighted price exhibiting large price drops upon generic entry and implicitly assumes instant diffusion of generics. Instead of changing our

FIGURE 6

CEPHRADINE PRICES

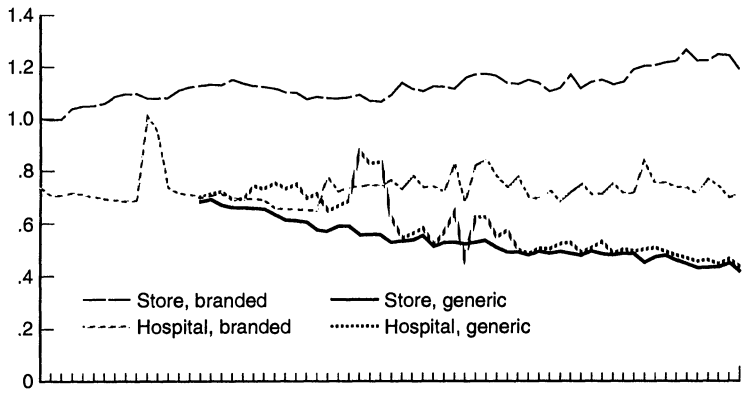
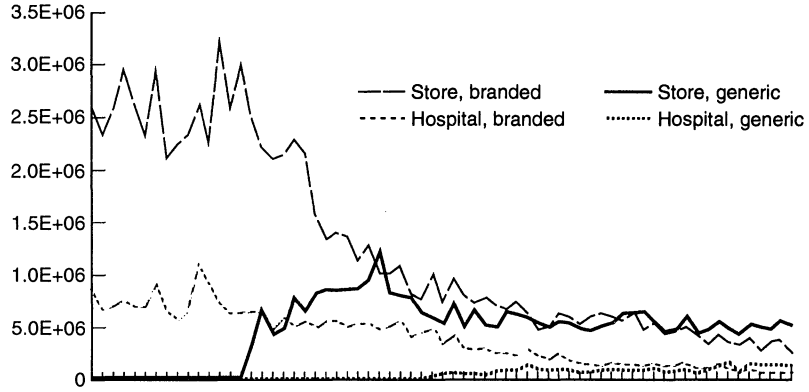


FIGURE 7

CEPHRADINE REVENUES



method of linking the price series, we explicitly modelled diffusion of generics to see if it seemed to be an important phenomenon in our case. A model with an indicator variable in the bottom level for the first six months after generic entry yielded qualitatively similar results.

Look now at the bottom level, the coefficient estimates on the log of the price ratio, in particular. The bottom-level estimates quite strongly support the notion that demand reacts to prices. The coefficients on the log of the ratio of prices are negative and highly significant. (t-statistics are 5.5 and 5.0, respectively, quite high given the sample size.) In sum, we interpret these results as meaning that price differences between branded and generic versions of the same drug are quite important in determining consumer behavior, but differences in the prices between different drugs seem to be less important, or perhaps harder to identify, although still relevant.

The conditional elasticities appear in Table 6 and the four-by-four matrix of unconditional elasticities appears in Table 7. We use the delta method to compute standard errors. We compute elasticities at the mean values for all the variables computed over the relevant sample period for each equation.

Look first at Table 6, the conditional elasticities. Recall that the only coefficient estimates used to calculate these elasticity estimates are from the bottom level. These

FIGURE 8

CEFACLOR PRICES

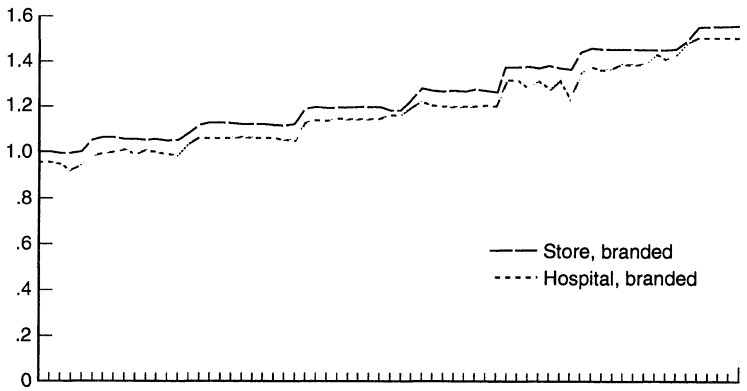
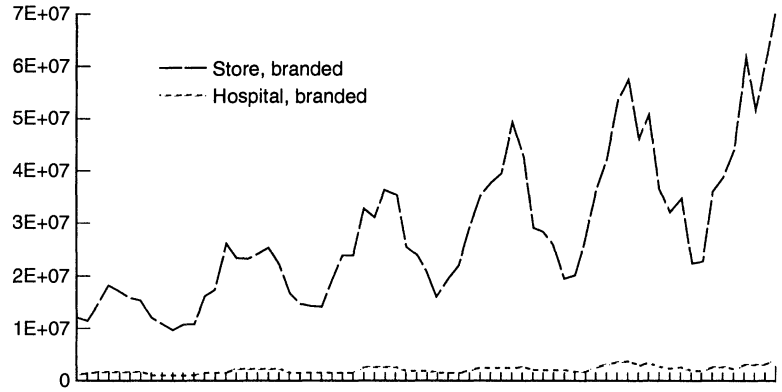


FIGURE 9

CEFACLOR REVENUES



elasticites are price elasticities between branded and generic versions of a drug holding expenditure on that drug constant. (Since expenditure, not quantity, is held constant, it is possible to obtain the unusual result that *both* quantities can decrease when a price is increased even though expenditure is held constant.) Note that for both drugs 1 and 3, own-price elasticities are negative and less than -1. Cross-price elasticities are positive. Also, generic own-price elasticities are always larger (in magnitude) than branded own-price elasticities—we might expect generic consumers to be more price sensitive than branded consumers.

Table 7, the unconditional elasticities, shows that our interpretation of the coefficient estimates is borne out by the elasticity estimates. Note fairly large and significant elasticities, in patterns similar to the conditional elasticities, in a block diagonal pattern, i.e., between products and their generic substitutes. In addition, the elasticities of drug 3 with respect to the prices of drug 1 are mostly significant (both statistically and economically). Note also that the branded own-price elasticity for drug 1 is small, especially relative to cross-price elasticities within drug 1. Our main conclusion is that demand for a branded (generic) drug seems to respond to price changes in the generic (branded) form of it, and sometimes to changes in price levels of close therapeutic substitutes in this particular segment of the pharmaceutical market. In other words, as a consumer moves down the decision tree, his choice seems to be somewhat affected

TABLE 4 Top-Level Estimates, Base Model

Drug		Estimates	Standard Errors[a]
	$\log(r)$	.2604	(.1020)
1	$\log(p_1)$	.2076	(.1845)
	$\log(p_3)$	−.3291	(.3552)
	$\log(r)$	.4073	(.1070)
3	$\log(p_1)$	.7910	(.1948)
	$\log(p_3)$	−.8952	(.3774)

$\log(q_D) = \eta_{0D} + \eta_{1D}S + \eta_{2D}t + \xi_D \log(r) + \delta_{D,1} \log(p_1) + \delta_{D,3} \log(p_3) + \epsilon_{1D}$

[a] These standard errors, along with those in subsequent tables, are not robust.

TABLE 5 Bottom-Level Estimates, Base Model

	Estimates	Standard Errors
$\log(r_1/p_1)$	−.0339	(.0739)
$\log(p_{10}/p_{11})$	−.1328	(.0242)
$\log(r_3/p_3)$	−.0274	(.0685)
$\log(p_{30}/p_{31})$	−.6689	(.1327)

$s_{D0} = \alpha_{0D} + \alpha_{1D}S + \beta_D \log(r_D/p_D) + \gamma_{D0}(\log(p_{D0}/p_{D1})) + \epsilon_{2D}$

by price differences when choosing between the two drugs that are fairly close therapeutic substitutes. Once that decision is made, price differences seem to be important in deciding between the branded and generic versions of the drug. Such a conclusion is important for understanding the demand for pharmaceuticals.

Stern (1996) estimates a demand system for pharmaceuticals and obtains results at variance with ours. Specifically, he finds low cross-price elasticities between branded and generic versions of the same drug and high cross-price elasticities between therapeutic substitutes. Both his dataset—he examines drugs in several therapeutic categories—and his estimation technique—he estimates a nested logit model—differ from ours, so it would be difficult to determine the source of the divergence. We do, however, think that an advantage of our approach is the free estimation of the cross-price elasticities of branded and generic versions of the same drug and would, therefore, place more confidence in those conditional elasticity estimates of our model. Certainly, further comparison of these two estimation techniques would be of interest.

In addition to estimating our base model with SUR, we tried different estimation techniques, SURIV and OLS equation by equation. We are interested in comparing these estimates to the SUR estimates and in checking the robustness of our general result. The parameter estimates for these two estimations appear in Tables 8 and 9. The instruments we use for SURIV are the previously mentioned ones based on the drugstore/hospital split and on the number of manufacturers.

Consider the SURIV estimates. Using hospital instruments, the top-level estimates no longer exhibit any significant group elasticities. The bottom-level estimates for drug 1, though, exhibit the same pattern as the SUR bottom-level estimates, although the

TABLE 6 Conditional Elasticities,[a] Base Model

Drug		Brand	Generic
1	brand	−1.16*	.21*
	generic	.35	−1.45*
3	brand	−1.99*	1.04*
	generic	1.88*	−2.96*

[a] The elasticity in the ith row and jth column is the demand elasticity of product i with respect to the price of product j conditional on drug expenditure.

* Significant at the 5% level.

TABLE 7 Unconditional Elasticities,[a] Base Model

Drug	1 Brand	1 Generic	3 Brand	3 Generic
1 brand	−.38*	1.01*	−.20	−.21
1 generic	.79*	−1.04*	−.09	−.10
3 brand	.52*	.53*	−1.93*	1.12*
3 generic	.21	.23*	2.00*	−2.87*

[a] The elasticity in the ith row and jth column is the demand elasticity of product i with respect to the price of product j.
* Significant at the 5% level.

price coefficient is smaller in magnitude. The coefficient for drug 3 is no longer significant. While differences might be expected given that we are instrumenting for prices in this estimation, the instrumenting is making the price coefficients smaller in magnitude, not larger as we would expect. The instruments may, in fact, be picking up demand shocks, such as cefadroxil's patent litigation. Using the number of manufacturers as an instrument, we produce results very similar to the SUR estimates. All of the same estimates are significant, and all but one have the same sign. Using hospital instruments, the SURIV estimates are less decisive than the SUR estimates. We therefore focus on the SUR estimates.

Look now at the OLS estimates. We have some strong correlations between residuals from different drugs, and such strong correlations could be the result of a shock common across drugs on which we do not have data or some nonprice effect that the drugs are having on each other. In any case, it is advisable for us to estimate these equations as a system using SUR given the correlations. Such high residual correlations might be an argument for including the other two drugs in our estimation, since there are also high residual correlations between cefadroxil equations and equations from the other drugs.

□ **Models with different sets of drugs.** We now consider alternative models with different sets of drugs. We estimate a model including cefadroxil, i.e., a model with the three first-generation cephalosporins we consider, and also a full model with all four drugs. We originally omitted cefadroxil (drug 2) from the analysis because its legal battles probably affected consumers' choices in a manner that we do not capture in our model. There are, however, arguments for considering a model with cefadroxil. Even if its coefficient estimates are not important or interpretable, its presence may

TABLE 8 Top-Level Estimates, Base Model, Different Estimation Methods

Drug		Hospital Instruments Estimates (Standard Error)	Manufacturer Instruments Estimates (Standard Error)	OLS Equation by Equation Estimates (Standard Error)
	$\log(r)$	.453 (.224)	.313 (.106)	.263 (.109)
1	$\log(p_1)$	−.746 (.628)	.276 (.175)	.231 (.196)
	$\log(p_3)$	.056 (.551)	−.166 (.207)	−.473 (.378)
	$\log(r)$	.509 (.152)	.350 (.130)	.403 (.120)
3	$\log(p_1)$	−.143 (.429)	.968 (.225)	.993 (.216)
	$\log(p_3)$	−.029 (.375)	−1.354 (.270)	−1.378 (.416)

$$\log(q_D) = \eta_{0D} + \eta_{1D}S + \eta_{2D}t + \xi_D \log(r) + \delta_{D,1} \log(p_1) + \delta_{D,3} \log(p_3) + \epsilon_{1D}$$

TABLE 9 Bottom-Level Estimates, Base Model, Different Estimation Methods

	Hospital Instruments Estimates (Standard Error)	Manufacturer Instruments Estimates (Standard Error)	OLS Equation by Equation Estimates (Standard Error)
$\log(r_1/p_1)$	.269 (.082)	−.162 (.095)	−.037 (.096)
$\log(p_{10}/p_{11})$	−.084 (.029)	−.316 (.046)	−.129 (.027)
$\log(r_3/p_3)$	.250 (.063)	.243 (.036)	.014 (.090)
$\log(p_{30}/p_{31})$	.022 (.098)	−.386 (.094)	−.563 (.172)

$$s_{D0} = \alpha_{0D} + \alpha_{1D}S + \beta_D \log(r_D/p_D) + \gamma_{D0}(\log(p_{D0}/p_{D1})) + \epsilon_{2D}$$

affect other coefficient estimates. As mentioned before, residuals from some of the equations are fairly highly correlated. Also, we believe it is the closest substitute to cephalexin and cephradine, based on therapeutic characteristics. We add the caveat that since generic cefadroxil entered almost two years later than the other two generic drugs, the sample size used to estimate the bottom-level equation for cefadroxil is much smaller than the other two, resulting in less precisely estimated coefficients. We also estimate a model with the three original drugs plus cefaclor (drug 4), a potential substitute. We chose to include it in one specification of our model because it might be a fairly close substitute to the three drugs we already have in the model. Including it in the analysis will let us know if its presence affects demand estimates for the other three drugs.

Tables 10 and 11 report the top- and bottom-level estimates for these two models estimated using SUR. In both of the models, drug 3 estimates at the top level are

TABLE 10 Top-Level Estimates, Models with Different Drugs

Drug		Drugs 1, 2, 3 Estimates (Standard Errors)	Drugs 1, 2, 3, 4 Estimates (Standard Errors)
	$\log(r)$	.278 (.108)	.283 (.109)
	$\log(p_1)$	.197 (.188)	.213 (.189)
1	$\log(p_2)$	−.074 (.168)	−.067 (.168)
	$\log(p_3)$	−.321 (.355)	−.356 (.355)
	$\log(p_4)$		−.326 (.660)
	$\log(r)$	.131 (.138)	.174 (.130)
	$\log(p_1)$	.875 (.240)	.966 (.225)
2	$\log(p_2)$	.987 (.215)	1.045 (.202)
	$\log(p_3)$	−.854 (.454)	−1.037 (.427)
	$\log(p_4)$		−2.461 (.790)
	$\log(r)$	.312 (.107)	.307 (.107)
	$\log(p_1)$	.839 (.190)	.809 (.188)
3	$\log(p_2)$	.472 (.169)	.443 (.168)
	$\log(p_3)$	−.912 (.360)	−.865 (.358)
	$\log(p_4)$		.744 (.655)
	$\log(r)$		1.144 (.053)
	$\log(p_1)$		.165 (.092)
4	$\log(p_2)$		.075 (.082)
	$\log(p_3)$		.043 (.174)
	$\log(p_4)$		−.487 (.323)

$$\log(q_D) = \eta_{0D} + \eta_{1D}S + \eta_{2D}t + \xi_D \log(r) + \delta_{D,1} \log(p_1) + \delta_{D,2} \log(p_2) + \delta_{D,3} \log(p_3) + \delta_{D,4} \log(p_4) + \epsilon_{1D}$$

TABLE 11 Bottom-Level Estimates, Models with Different Drugs

	Drugs 1, 2, 3 Estimates (Standard Errors)	Drugs 1, 2, 3, 4 Estimates (Standard Errors)
$\log(r_1/p_1)$	−.042 (.072)	−.043 (.071)
$\log(p_{10}/p_{11})$	−.140 (.024)	−.140 (.024)
$\log(r_2/p_2)$	.203 (.059)	.194 (.058)
$\log(p_{20}/p_{21})$	−.058 (.141)	−.117 (.135)
$\log(r_3/p_3)$	−.029 (.068)	−.044 (.067)
$\log(p_{30}/p_{31})$	−.671 (.132)	−.712 (.129)

$s_{D0} = \alpha_{0D} + \alpha_{1D}S + \beta_D \log(r_D/p_D) + \gamma_{D0}(\log(p_{D0}/p_{D1})) + \epsilon_{2D}$

significant and reasonable. Drug 2 estimates are significant but have the wrong sign and are difficult to interpret. Others are not significant. At the bottom level, estimates change very little for drugs 1 and 3 from the base model. The bottom-level price coefficient for drug 2 is not significant. Again, we find in both of these models that price effects are fairly strong at the bottom level and somewhat weaker at the top level. Drug 2 results are hard to interpret.

Table 12 is the seven-by-seven matrix of elasticities from the model with all four drugs. Elasticities for drug 2 are problematic. The elasticities within drug 2 are strange, particularly the large, significant, and positive own-price elasticity of the branded version, as well as cross-price elasticities involving drug 2 and other drugs. Several are large and significant, some positive and some negative. Aside from drug 2 elasticities, our main qualitative conclusion remains: demand reacts fairly strongly to price changes in generic substitutes and somewhat to price changes in therapeutic substitutes in this particular segment of the pharmaceutical market.

In an earlier version of this article we estimated a full four-stage decision tree to determine the extent to which substitution to goods outside this smaller system might be affecting our results. (Goldberg (1995) discusses the bias associated with the omission of outside goods.) We estimated two additional layers of the demand system, one representing the choice of the class of drugs, cephalosporins, among all antibiotics, and the second representing the choice of our drugs among all cephalosporins.[21] The qualitative result—high own- and cross-price elasticities within a drug and low cross-price elasticities between drugs—was more pronounced in this model.

□ **A price index calculation.** The estimated demand system and elaticities that we present here are of interest themselves, of course, but they can also be used for the calculation of a therapeutic group price index, based on estimated parameters in the demand system.

Generics are an instance of the "new-goods problem" in price index construction, a topic receiving renewed attention as the potential biases inherent in procedures used by official statistical agencies have come under scrutiny. When new products appear in the marketplace, standard practice in the United States and most other countries has been to make no direct comparison between new products and old products: once

[21] The bottom two levels of the demand system remain the same, except that revenue in the "top" equation is now total revenue for the drugs in our sample, not for all cephalosporins. We instrumented for prices in the top two levels with cost-shifting instruments, wages in the chemical industry, and the PPI for chemicals.

TABLE 12 Unconditional Elasticities,[a] Model with All Drugs

Drug	1 Brand	1 Generic	2 Brand	2 Generic	3 Brand	3 Generic	4 Brand
1 brand	−.39*	1.02*	−.06	−.06	−.22	−.23	−.22
1 generic	.82*	−1.07*	.01	.00	−.09	−.11	−.10
2 brand	.79*	.72*	1.06*	2.30*	−.81*	−.75*	−2.38*
2 generic	4.25*	2.14*	3.88	−4.34	−4.41*	−2.50*	−.08*
3 brand	−.28	−.26	.40*	.43*	−1.96*	1.12*	.49
3 generic	−.18	−.15	−.04	.01*	2.14*	−2.97*	.26
4 brand	.34*	.08*	.09	.00	.14	.06*	−.49

[a] The elasticity in the *i*th row and *j*th column is the demand elasticity of product *i* with respect to the price of product *j*.

* Significant at the 5% level.

identified, new products are included in the basket of goods used to calculate a price index, but only movements in their prices *after* the date of entry contribute to changes in the aggregate index. Any absolute price differential between new goods and comparable existing goods is ignored. This may be a reasonable procedure for truly new goods, for which there are no comparable existing products, but it may not be appropriate for many products for which close substitutes are available. Generic versions of existing drugs are a case in point: the FDA certifies them to be perfect substitutes for the existing branded version (in the sense of being "bioequivalent"), while until very recently the principal producer of price statistics, the Bureau of Labor Statistics (BLS), has treated them as completely unrelated products.

The theoretical solution to the new-goods problem is well known (Hicks, 1940; Fisher and Shell, 1972): products appearing in period 1 should be "linked in" to the aggregate index using a period-0 reservation price at which the quantity demanded is just equal to zero. To compute the implicit price decline for the new good at the moment of entry requires an estimate of this reservation price. We use the estimated demand equations to compute these prices for the new generic versions of cephalexin, cefadroxil, and cephradine, and we compare the resulting price indices with those that would be obtained using alternate methods. See Hausman (1994) for a similar exercise involving breakfast cereal.

Table 13 presents results. As a basis for comparison, we first compute a price index for the four drugs using a procedure that attempts to replicate the way the BLS computes the Producer Price Index (PPI): this is a Laspeyres index with a fixed basket of goods and fixed weights based on revenue shares from the base period.[22] We update the basket of goods and their item weights in the index twice: once in 1986, fourth quarter, and then again in 1989, fourth quarter, which is twice as fast as the BLS revises its samples. Nonetheless, the resulting price index captures the appearance of generics only with long lags and with relatively small weights. Despite the much lower prices for generics and their rapid gains in market share, this fixed-weights Laspeyres index grows at an annual rate of 8.65%. The size of the bias generated by the fixed-weights approach can be inferred from the growth rate of a chained Paasche index that makes no direct comparisons between brand and generic versions of the same drug, but continuously updates the item weights (line 2 of Table 13). The difference between the two is large: the chained Paasche index grows at 6.69% per year, implying an upward bias imparted by the fixed-weights approach of 2% per year.

[22] The rather serious problems with this procedure and resulting large upward biases in price indices for pharmaceutical products have been documented elsewhere (Berndt, Griliches, and Rosett, 1993; Griliches and Cockburn, 1994). The BLS is revising its treatment of pharmaceutical products in the CPI and PPI.

TABLE 13 Price Indices

Index	Average Annual Growth Rate
Fixed-weights Laspeyres	8.65
Chained Paasche	
No link	6.69
"FDA" link	4.35
Reservation price link	5.37

Most importantly, however, this procedure "links out" the very substantial price declines experienced by purchasers who switch to generics once they become available. Taking the U.S. Food and Drug Administration (FDA) at its word, sales of generics are just lower-priced transactions in existing products. Under this assumption, which will be used in the future by the BLS in computing the PPI for pharmaceuticals, generics can be "linked in" simply by averaging prices over brand and generic versions of each drug. A chained Paasche index across the four drugs using this assumption grows at 4.35% per year, which is less than half of the annual growth rate of the fixed-weights Laspeyres index. The fact that not all purchasers switch to the generic version makes the "FDA" assumption somewhat problematic, however, and a better alternative may be to use the demand estimates computed above, which treat brand and generic versions of the drug as differentiated products. In the last line of Table 13 we give the results of computing a chained Paasche index where generics are linked in using the implicit price declines computed from the demand estimates above. This index rises at an annual rate of 5.37%, which we believe gives a better indication of the impact of patent expirations on price changes and welfare.

5. Conclusion

■ The results from our model of demand as a multistage budgeting problem lead us to our basic conclusion that there is fairly high demand elasticity between generic substitutes, products with chemically identical active ingredients produced by different companies, in the drugs we observed. Demand elasticity was smaller but often significant between therapeutic substitutes, chemically distinct drugs that can be used to treat many of the same conditions, in the drugs we observed. Taken in conjunction with our knowledge of the structure of the prescribing and dispensing process, our results suggest some price sensitivity at both the prescribing and dispensing stages.

We think these results are important for a number of reasons. First, these elasticity estimates are of interest for the standard reasons: they could be used to determine firm conduct in this industry, say, or help in the construction of price indices. But due to current policy interest in the pharmaceutical industry and academic interest in the pharmaceutical purchasing process, these elasticities take on additional interest and importance. Our results suggest some price sensitivity at both stages of the purchasing process, but we see stronger evidence at the dispensing stage than at the prescribing stage. Depending on the degree to which health care policy makers believe these products are close substitutes in a technological sense, our results could point to possible scope for policy reforms, such as more effective dissemination of information on prices to physicians. Since we think there have been major changes in the industry and the market for pharmaceuticals over the last few years, it would be interesting to perform studies using more recent data to see what effects these changes may have had.

References

ANDERSON, S.P., DE PALMA, A., AND THISSE, J. *Discrete Choice Theory of Product Differentiation.* Cambridge, Mass.: MIT Press, 1992.

BERNDT, E., GRILICHES, Z., AND ROSETT, J. "Auditing the Producer Price Index: Micro Evidence from Prescription Pharmaceutical Products." *Journal of Business and Economic Statistics,* Vol. 11 (1993), pp. 251–264.

BOSTON CONSULTING GROUP. "The Changing Environment for U.S. Pharmaceuticals." Mimeo, 1993.

CAVES, R., WHINSTON, M., AND HURWITZ, M. "Patent Expiration, Entry and Competition in the U.S. Pharmaceutical Industry." *Brookings Papers on Economic Activity: Microeconomics,* 1991, pp. 1–66.

DEATON, A. AND MUELLBAUER, J. *Economics and Consumer Behavior.* Cambridge: Cambridge University Press, 1980.

Drug Facts and Comparisons. St. Louis: J.P. Lippincott Company, 1991.

FEENSTRA, R. "Generics and New Goods in Pharmaceutical Price Indexes: Comment." Mimeo, 1995.

FISHER, F. AND SHELL, K. *The Economic Theory of Price Indices.* New York: Academic Press, 1972.

FRANK, R. AND SALKEVER, D. "Pricing, Patent Loss and the Market for Pharmaceuticals." *Southern Economic Journal,* Vol. 59 (1992), pp. 165–179.

——— AND ———. "Generic Entry and the Pricing of Pharmaceuticals." NBER Working Paper no. 5306, 1995.

GOLDBERG, P.K. "Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry." *Econometrica,* Vol. 63 (1995), pp. 891–951.

GORMAN, W. "Two Stage Budgeting." Mimeo, 1971.

GRABOWSKI, H. AND VERNON, J. "Brand Loyalty, Entry and Price Competition in Pharmaceuticals After the 1984 Drug Act." *Journal of Law and Economics,* Vol. 35 (1992), pp. 331–350.

GRILICHES, Z. AND COCKBURN, I. "Generics and New Goods in Pharmaceutical Price Indexes." *American Economic Review,* Vol. 84 (1994), pp. 1213–1232.

HAUSMAN, J. "Valuation of New Goods Under Perfect and Imperfect Competition." MIT Department of Economics Working Paper, 1994.

———, LEONARD, G., AND MCFADDEN, D. "A Utility-Consistent Combined Discrete Choice and Count Data Model: Assessing Recreational Use Losses Due to Natural Resource Damage." *Journal of Public Economics.* Vol. 56 (1995), pp. 1–30.

———, LEONARD, G., AND ZONA, D. "Competitive Analysis with Differentiated Products." *Annales d'Economie et de Statistique.* Vol. 34 (1994), pp. 159–180.

HELLERSTEIN, J. "Post-Patient Prescription Pharmaceuticals." Ph.D. dissertation, Department of Economics, Harvard University, 1994.

HICKS, J. "The Valuation of Social Income." *Economica,* Vol. 7 (1940), pp. 105–124.

New York Times. "A Shift of Power in Pharmaceuticals," May 9, 1994, p. A1.

Physicians' Desk Reference, New York: Medical Economics Data, 1993.

SCOTT MORTON, F. "Barriers to Entry, Brand Advertising and Generic Entry in the U.S. Pharmaceutical Industry." Stanford GSB Working Paper, 1995.

STEELE, H. "Monopoly and Competition in the Ethical Drug Market." *Journal of Law and Economics,* Vol. 5 (1962), pp. 142–143.

STERN, S. "Product Demand in Pharmaceutical Markets." Mimeo, Sloan School of Management, MIT, 1996.

TEMIN, P. *Taking Your Medicine.* Cambridge, Mass.: Harvard University Press, 1980.

WALKER, H. *Market Power and Price Levels in the Ethical Drug Industry.* Bloomington, Ind.: Indiana University Press, 1971.

WIGGINS, S. AND MANESS, R. "Price Competition in Pharmaceuticals: The Case of Antiinfectives." Mimeo, Department of Economics, Texas A&M University, 1995.