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The Effect of Bargaining Power Determinants on Pharmaceutical Prices

Abstract

This paper provides insights into the determinants of bargaining power and how they affect drug prices. Our data show that drug prices vary across buyers and time periods. We estimate a structural bargaining model where drug suppliers and buyers engage in bilateral bargaining over drug prices. Our estimation results show that drug buyers hold, on average, 55% of the bargaining power. We also find that bargaining power can imply a range of drug prices. Differences in bargaining power explains large price heterogeneities across buyers, drug classes, and time periods. Additionally, of the drug price variation that is explained by bargaining power, differences across buyers rather than changes over time are more important. We examine buyer and seller characteristics that determine bargaining power and evaluate how changes in these bargaining power determinants affect bargaining power and prices. We find that transaction-specific determinants (such as transaction volume) and business relationships between buyers and sellers (such as buyer's loyalty and multiple drug purchases from the same seller) exert the strongest effects on improving buyer bargaining power and reducing drug prices. For example, an 10% increase in transaction volume, buyer's loyalty, and multiple drug purchases strengthens buyer's bargaining power and results in a drug price reduction of 12%.

JEL-Codes: L100.

Keywords: bargaining power, determinants of bargaining power, drug prices, drug price variation, business relationship between buyers and sellers.

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1 Introduction

In many markets, different buyers pay different prices for the same good rather than paying a uniform market price. The specific prices are determined by bargaining, and the relative bargaining power between buyers and sellers plays an important role in negotiating these prices (see Crawford and Yurukoglu (2012) and Grennan (2013)).[1] Prominent studies have shown that heterogeneity in bargaining power is important in explaining price variations (see Grennan (2013)). For example, stronger bargaining power on the buyer side can result in "secret price discounts" and "rebates" (see also Armstrong (2006)). The question arises: What are the determinants of bargaining power between buyers and sellers, and to what extent do these determinants affect bargaining power and, in turn, negotiated prices?

Several empirical papers concentrate on the effects of market characteristics (such as demand, costs, and competition) on bargaining outcomes.[2] Until now, however, little is known about how other determinants such as transaction-specific characteristics and business relationships between buyers and sellers (such as loyalty, transaction volume discounts, etc.) affect bargaining power and prices. More insight on this topic is needed, as it can provide further guidance for managers in negotiating better bargaining deals.

Bargaining and negotiated price discounts form the center of many policy debates, especially in drug and health markets, and the effect of bargaining power determinants on prices plays a critical role in these debates. Many drugs have, at times, experienced price increases of hundreds or thousands of percent.[3] This is a serious concern since drugs are indispensable to society, as they can treat severe diseases and improve quality of life. There are different viewpoints on such price explosions; drug sellers and buyers often deflect responsibility to each other. More specifically, sellers claim that buyers (such as pharmaceutical benefit managers engaging in large transactions) become increasingly powerful due to increased transaction size and consolidation,

[1] Bargaining studies distinguish occasionally between "bargaining power" and "bargaining ability." We use the term bargaining power to relate to specific negotiated price outcomes. For example, complete bargaining power on the buyers' side results in price equal to marginal cost. Complete bargaining power on the sellers' side results in Bertrand-Nash outcomes that correspond to "take it or leave it offers" (see also Porter (1980) and Grennan (2013) for further information).

[2] For example, Ellison and Snyder (2010) find that large buyers (U.S. drugstores) of antibiotic drugs receive a modest price discount only if suppliers are in competition.

[3] Many U.S. states have filed lawsuits against generic manufacturers, accusing them of colluding to raise prices substantially (see https://www.pharmacytimes.com/resource-centers/reimbursement/antitrust-lawsuit-targets-20-generic-drug-manufacturers-15-industry-executives-over-medication-pricing).

which potentially increases their bargaining strength such that sellers are forced to grant discounts and rebates. Drug manufacturers claim they must increase list prices in order to mitigate the impact of these rebates.[4] These special offers, then, come at a cost to smaller buyers that have less bargaining power and suffer from significantly higher prices. In contrast, large buyers argue that large transactions are essential to achieve bargaining strength and keep drug prices low. Buyer size and transaction size, however, are only two of many buyer, seller, and market characteristics that can determine relative bargaining power. This study aims to further our understanding about the effect of bargaining power determinants on negotiated prices in the pharmaceutical drug market.

We make novel use of a dataset that contains detailed, transaction-specific bargaining information. This detailed data enable us to include specific bargaining determinants–such as transaction-specific and business relationship characteristics between buyers and sellers–into the analysis. The pharmaceutical drug market provides a natural setting for our purposes, since drug prices are usually negotiated between drug suppliers and buyers. Moreover, the drug market is characterized by large price variations across buyers and over time.

The empirical estimation of the effect that buyer and seller bargaining power has on drug price variation is beset with several difficulties. One empirical challenge is that bargaining power is usually unobserved, which requires a model that describes how cost, willingness to pay, and bargaining power translates into prices. Moreover, negotiated transaction-specific prices, or wholesale prices, are rarely observed. Therefore, many studies rely on list prices or retail drug prices that encompass the entire value chain. We observe detailed, transaction-specific bargaining information, including the negotiated price, which allows us to evaluate the effects of specific buyer, seller, and transaction channels on the bargained price. A further empirical challenge is that negotiated quantities and prices are usually available only in aggregate form for a specific period (such as month or year). In this time period, however, multiple transactions between buyers and sellers will have been conducted. As such, the aggregation of individual transactions imposes limitations on working out the effects of buyer-, seller-, and transaction-specific determinants on bargaining power and prices. Given the common use of aggregated transaction data, it is surprising that

[4]For instance, Humalog manufacturer Eli Lilly claims the net price it receives for the drug has declined over the last five years, while the list price has skyrocketed. See page 16 of https://investor.lilly.com/static-files/ae580ba4-5d84-4862-a5d2-99a1d784d7a8.

this topic has not yet received significant attention.

A strength of our database is that it encompasses detailed information on individual drug purchase transactions. The transaction-specific information provides new insights, and it enables us to establish measurements that reflect the business relationships between buyers and sellers. The detailed drug purchase records stem from a database ("Banco de Preços Saúde") that contains wholesale drug transactions in Brazil. The Brazilian market provides an appropriate setting for several reasons. First, the institutional characteristics in the Brazilian market provide us with detailed information on transaction records that help us examine bargaining power. We observe detailed information on each bargaining transaction, including wholesale prices rather than list prices or retail drug prices. We observe transaction details, such as dates, participants, transaction volumes, transaction frequency, repeated transactions, loyalty, etc., which enables us to thoroughly evaluate the effects of a number of specific bargaining power determinants. Second, Brazil experienced health policy reforms that require public recording of bargaining transactions in the drug markets (Kohler et al. (2015)). Hence, the public administration and registration of bargaining outcomes enforces the reliability of transaction information, which ensures quality and reliability of bargaining information. Third, Brazil is the sixth-largest pharmaceutical market in the world, with sales exceeding $30 billion in 2017.[5]

We focus on antihypertensive drugs that are generally used to treat cardiovascular diseases. Antihypertensive drugs are widely prescribed, and they exhibit significant price variations across buyers, time, and drug classes. This feature makes them a suitable drug to help us explain the determinants of bargaining power and price. More specifically, we consider antihypertensive drugs within five common drug classes over a time period from January 2015 through December 2016.[6]

Our summary statistics show large price variations across buyers and time periods for the same drugs. The existence of these large price variations suggests that bargaining power is a relevant feature to explain price dispersion. Additionally, we find that cross-sectional price variation across buyers is consistently higher than the price variation over time, suggesting that bargaining differences across buyers might play a critical role in determining the prices they face. We establish a bargaining model to empirically estimate bargaining power across buyers and time periods. We

[5]https://www.worldatlas.com/articles/countries-with-the-biggest-global-pharmaceutical-markets-in-the-world.html

[6]More details are mentioned in the next section.

build on the Nash Bargaining model by Horn and Wolinsky (1988), where prices are set in the presence of competition, and each buyer negotiates with each seller separately and simultaneously. On the demand side, we use a random coefficient model, similar to Berry et al. (1995), that formulates drug choices for physicians and patients. Our demand estimation results support heterogeneous willingness to pay preferences among buyers. The estimated demand parameters are then used to calculate elasticities, expected quantities, and manufacturer and buyer surplus measures. These are needed for the estimation of the bargaining model between buyers and sellers. The estimation of the bargaining model shows that drug buyers hold, on average, 55% of the relative bargaining strength. Most notably, the bargaining power estimates show large heterogeneities across buyers, drugs, and time periods. Our results show that bargaining strength is particularly powerful at explaining price variations across buyers and drug classes compared to variations across time. More specifically, 43% of the drug price variation is due to differences in bargaining strength across buyers. Next, we show that transaction-specific determinants (such as transaction volume) and business relationships between buyers and sellers (such as buyer's loyalty and multiple drug purchases from the same seller) have strong effects on bargaining power and prices. We report how changes in bargaining determinants affect bargaining power and prices. For instance, a 10% increase in quantity purchased in a transaction can strengthen buyer bargaining power and result in a price reductions of over 6%. However, we find that the effects of each of the determinants on bargaining power and prices vary across drug classes. We provide predictions on price savings that can be achieved once buyers invest in improving specific bargaining power determinants.

Our study is closely related to empirical bargaining studies, including Crawford and Yurukoglu (2012), Grennan (2013), Gowrisankaran et al. (2015), Ho and Lee (2017), and Dubois et al. (2018). Several studies in this area have shown that relative bargaining strength between sellers and buyers can have large effects on prices (see Grennan (2013), Grennan (2014), Bennett (2013), Dranove et al. (2007), Ho (2009), and Dafny (2010)). Most bargaining papers use list prices, while only a few studies have access to negotiated prices. These include Hastings (2008) on gasoline stations, Dafny (2005) on health insurance, and Grennan (2013) and Grennan (2014) on cardiac medical stent devices. Our study is most closely related to the latter two studies by Grennan, who finds large differences in relative bargaining abilities between stent manufacturers

and hospitals. These studies also provide evidence for time-varying bargaining abilities, which is attributed to possible learning effects over time. As mentioned earlier, our study differentiates itself from previous bargaining studies, as it makes use of bargaining information that is specific to single transactions between buyers and sellers. We also observe the negotiated drug prices from single drug transactions; hence, our drug transaction prices are not aggregated over time. This allows us to explore buyer-seller relationship characteristics such as loyalty rebates, discounts, and repeated transactions, among others.

Our study also relates to studies that address and evaluate drug pricing policies, such as Chaudhuri et al. (2006), Kaiser et al. (2014), and Dubois et al. (2018). In this context, several studies show that uniform pricing increases price transparency and competition, leading to price reductions, while other studies (Grennan (2013)) show that price discrimination can help buyers with high bargaining power and result in lower prices than if there had been uniform pricing.

2 Data Sources and Descriptives

This study focuses on hypertension and cardiovascular diseases, such as high blood pressure, heart attacks, and strokes. We concentrate on generic antihypertensive drug prescriptions for several reasons. First, antihypertensive drugs are commonly prescribed across the world, so insights gained on the Brazilian market provide insights for other markets in the world as well. Second, antihypertensive drugs have clearly defined characteristics, including mechanisms of action, efficacies, side effects, and patient characteristics for first-line treatments. These clear definitions facilitate the classification of drugs into drug classes. In this regard, we consider five antihypertensive drug classes: alpha blockers, beta blockers, calcium channel blockers (CCBs), diuretics, and other drugs. Each drug class contains three to five molecules (from here onward referred to as drugs), so this adds up to a total of 20 drugs that we use in our study (see Table 1). It should be noted that antihypertensive drugs are commonly considered and prescribed as substitutes rather than complements.[7] Antihypertensive drugs generally represent closer substitutes within a drug class rather than across drug classes (Jarari et al. (2016)). Therefore, the set of alternative drugs is drug class specific. This feature is especially important for our demand estimation, which builds on the assumption that drugs are substitutes. Patients may switch between antihyperten-

[7] The cross-price elasticities reported in Appendix A support this classification.

sive drugs in a sequential manner depending on efficacy, side effects, and patient characteristics. Hence, at one time, patients usually take one, not multiple, antihypertensive drug. This is different from other drugs, such as pain killers, that have a complementary part since patients often use combinations of drugs. Finally, antihypertensive drugs are inexpensive to produce and cost only a few cents per tablet. Therefore, any marginal cost changes over time are minimal and will not crucially affect price changes. This justifies the isolation of price changes to changes in bargaining power.

We focus on the Brazilian market, since institutional characteristics provide us with rarely available transaction information that is useful for the examination of bargaining power. We use a novel database ("Banco de Preços Saúde") that records detailed drug bargaining information between drug manufacturers and purchasers in Brazil. The database covers the January 2015 through December 2016 period and contains detailed drug transaction prices (rather than list prices or retail drug prices) and transaction volumes as well as the names of buyers and sellers, the date of the transaction, the name of the drug, quantities, dosages, and formulation (tablet, injectable, etc.).

Brazilian drug buyers are typically municipalities that publicly report bargaining transactions with the government.[8] Each municipal government has the autonomy to purchase on behalf of health providers located in that municipality.[9] They act as separate buyers engaging in bilateral bargaining deals with drug manufacturers. Drug manufacturers are typically domestic firms that sell multiple drugs. We complement the transaction data with demographic data taken from the Brazilian census.

We observe multiple transactions between drug sellers and buyers. It is noteworthy that multiple transactions are conducted in one year for the same drug and that transaction prices change.[10]

Drugs are prescribed and sold at different dosages, which contain different amounts of the active ingredient. For example, atenolol tablets (a beta blocker) are prescribed in dosages of 50mg or 100mg and sold for different prices. In order to be able to include different dosages of

[8]One reason why transactions are publicly recorded is that municipal governments are part of the *Sistema Único de Saúde* national health system.

[9]There are also federal, state, and private (typically international nongovernment organizations) buyers. However, the city-level buyers make up 74% of all transactions in the relevant time period.

[10]This statement has been made in other studies, see Luiza et al. (2017). They claim that while contract prices are typically valid for one year, they are usually renegotiated in the interim.

the same drug into the empirical analysis, it is common practice to normalize dosage amounts based on a defined daily dosage (DDD). The DDD is the average daily dose prescribed to adults. The measure is defined and provided by the World Health Organization.[11] In the remainder of the study, all prices and quantities are expressed in DDDs. To ensure we do not lose important information that might be related to the dosage amount, we calculated the average and median prices across different dosages for all of the drugs in the beta blocker class. There was no price trend recognizable across dosages. Additionally, the price variation behavior for individual dosage amounts is the same as the price variation measured in DDD's.[12]

Table 1, columns 1 through 5, shows summary statistics on prices across drugs. Throughout the paper, prices are expressed in Brazilian Reals.[13] The mean is frequently higher than the median, which is indicative of a right-skewed price distribution. Moreover, it is noteworthy that the ratio of the standard deviation to the mean varies greatly across drugs. The standard deviation is often larger than the median, supporting the fact that there is a large degree of price variation in the market.

In order to provide further insights into the price variation, we build on two price dispersion measures commonly used in previous studies (such as Grennan (2013) and Grennan (2014)). The first measure captures cross-sectional drug price variation across buyers (PV_{buyer}). The PV_{buyer} measure is constructed by restricting the sample to the median time period (that is, March 2016) and then dividing the standard deviation of a drug's price across buyers by the average of that drug's price across buyers. Column 6 of Table 1 illustrates that the cross-sectional drug price variation measure ranges from 0.2 to 1.517, with an average of about 0.822. Hence, on average, the standard deviation is close to the mean, which is representative of a large price dispersion. (For perspective, the cross-sectional price variation for cardiac stents in the U.S. ranged from 0.08 to 0.32, with an average of 0.13 (see Grennan (2013))). The PV_{buyer} measure supports the fact that buyers are paying largely different prices for the same drugs. Robustness checks confirm that the drug price variation across buyers (PV_{buyer}) is similar across different tablet dosages[14]. Therefore, price variations are unlikely explained by different amounts of the active ingredients.

[11] For example, the DDD for atenolol is 75mg. So, transactions of 50mg atenolol tablets count as two-thirds of a DDD and 100mg atenolol tablets count as four-thirds of a DDD.

[12] See Table 13 through Table 17 in Appendix B.

[13] Currently, a U.S. Dollar is worth about 4 Brazilian Reals.

[14] See Table 13 through Table 17 in Appendix B.

At this moment, it is unclear why the transaction prices are so different across buyers and to what extent price variations can be explained by variations in bargaining power. These aspects will be addressed later in our analysis.

The second price variation measure, PV_{time}, considers the average price across buyers and measures its variation over time. In accordance with the previous measure, the standard deviation of a drug price across time is then divided by the corresponding mean across periods. The PV_{time} measure returns a large amount of prices variation over time, ranging from 0.073 to 0.777, with an average of 0.394.

It should be recognized that the cross-sectional price variation across buyers (PV_{buyer}) is more than twice as the price variation over time (PV_{time}). Hence, drug prices vary more across buyers than they vary across time. This comparison provides some indication that buyer-specific features deserve special attention (compared to demand and supply changes over time) when explaining bargaining power and predicting prices. The price variations across buyers and time can be caused by cost, competition, demand, learning, and bargaining power arguments. We return to disentangling the price variation in our empirical model estimation.

3 Empirical Model

The goal is to structurally estimate the bargaining power strength that determines the split of surplus between the seller and buyer. We allow bargaining power to vary across time and drugs so we are able to analyze the effect of bargaining power across buyers and time on price variation. Finally, we use the retrieved bargaining power parameters to explicitly explore the determinants of bargaining power and price variation.

We formulate a Nash Bargaining model similar to Horn and Wolinsky (1988) in which drug sellers maximize profits and buyers maximize consumer welfare.[15] Each buyer negotiates separately and simultaneously with a finite number of drug sellers. Prices are set to maximize the Nash product of seller profits and buyer consumer surplus, taking prices of other products in the buyer's choice set as given. The outcome of each negotiation satisfies the bilateral Nash bargaining solution, where prices form a Nash equilibrium of bilateral Nash bargaining problems such

[15]Other empirical studies that build on this model include Crawford and Yurukoglu (2012), Grennan (2013), Gowrisankaran et al. (2015), Ho and Lee (2017), and Dubois et al. (2018).

that no party wants to renegotiate.

We define a "market" as the interaction between buyers and sellers in a particular city ($c \in C$) and a monthly time period ($t \in T$) for drug ($j \in J$). On the supply side, drug manufacturers offer a set of drugs J_{ct} in a city during a specific period. Similarly, the set of cities where drug j is sold at period t is given by J_{jt}.

On the demand side, patients $i \in I_{ct}$ arrive exogenously in each city and each period. Hence, we define a geographic market as a city-period pair.

Within a given market, patients are treated by physicians who choose which drugs to prescribe. In selecting a drug, physicians choose from a set of drugs within one of the five particular drug classes mentioned earlier (i.e., alpha blockers, beta blockers, calcium channel blockers, diuretics, and other drugs). It is important to note that in choosing a particular drug, physicians account for both their own preferences as well as hospital/city and patient preferences. This approach has the benefit of intuitively matching the doctors' decision process, and it accommodates the fact that the choice sets of available drugs vary across hospitals and cities.[16] Physicians can vary in their preferences for which drug would be best to treat a given patient, as described by an idiosyncratic component (ϵ_{ijct} introduced later in the model).

On the buyer side, each city government acts on behalf of its health providers (hospitals and physicians), which is consistent with the data and institutional market characteristics. The drug buyers negotiate with drug manufacturers on the quantity and prices for each drug.

The model is formulated as a two-stage game. In the first stage, drug sellers and drug buyers negotiate on drug prices and quantities. In the second stage, doctors decide on prescriptions as patients arrive.

3.1 Bargaining Power

Each buyer, in a given month, seeks to satisfy the demand of its patient population by sourcing enough supply of any given drug within each drug class. Each bilateral price maximizes the weighted product of the seller's profit and a buyer's surplus:

$$\underset{p_{jct}}{max}\ [q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j) - d_{jct}]^{b_{jt}(c)}[q_{jct}(\boldsymbol{p}_{ct})\pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}]^{b_{ct}(j)}. \tag{1}$$

[16] In this regard, the agent i could also be thought of as a mix between the patient and physician.

The first term in Equation (1)—$[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j) - d_{jct}]$—captures the overall surplus of the seller, where p_{jct} is the price per DDD, q_{jct} is the quantity measured in DDDs, $\boldsymbol{p}_{ct}$ is a vector of prices for all other drugs, mc_j is the marginal cost of drug j, which is considered to be time-invariant, as explained earlier. The seller's disagreement payoff ($d_{jct} = \pi_{jt}(\boldsymbol{p}_{jt}; J_{jt}\backslash\{c\})$) considers the payoff excluding city c.

The second term in Equation (1)—$[q_{jct}(\boldsymbol{p}_{ct})\pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}]$—captures the surplus of the buyer. The surplus of the buyer is denoted by π_{ct} and $d_{cjt} = \pi_{ct}(\boldsymbol{p}_{ct}; J_{ct}\backslash\{j\})$ refers to the buyer's disagreement payoff if drug j is not purchased.

Last, $b_{jt}(c), b_{ct}(j)$ are the bargaining power parameters of the seller and buyer, respectively. The estimation of these parameters forms the main interest of our study.[17]

Taking first-order conditions of Equation (1) with respect to the drug price and solving for the bargained price, we get:

$$p_{jct} = mc_j + \frac{b_{jt}(c)}{b_{ct}(j) + b_{jt}(c)} \left[\left(1 + \frac{\partial q_{jct}}{\partial p_{jct}} \frac{p_{jct} - mc_j}{q_{jct}} \right) \left(\pi_{ct} - d_{cjt} \right) + p_{jct} - mc_j \right]. \tag{2}$$

Equation (2) implies that in order for price to be above marginal cost, it must be the case that $\left(1 + \frac{\partial q_{jt}}{\partial p_{jt}} \frac{p_{jt} - mc_j}{q_{jt}}\right) > 0$, or put differently that $\left(\frac{\partial q_{jt}}{\partial p_{jt}} \frac{p_{jt} - mc_j}{q_{jt}}\right) \in [-1, 0]$ and that $\pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}(\boldsymbol{p}_{jt}; J_{ct}\backslash\{j\}) > 0$ (see Grennan, 2013).[18]

Rearranging Equation (2), the relative bargaining power between the seller and buyer of drug j and city c at time period t is given by:

$$\frac{b_{jt}(c)}{b_{ct}(j) + b_{jt}(c)} = \frac{p_{jct} - mc_j}{\left(1 + \frac{\partial q_{jct}}{\partial p_{jct}} \frac{p_{jct} - mc_j}{q_{jct}}\right) \left(\pi_{ct} - d_{cjt}\right) + p_{jct} - mc_j}. \tag{3}$$

Equation (3) shows that the relative bargaining power between seller and buyer depends on the value-added terms that represent the additional surplus to the buyer from purchasing drug j and the additional profit to the seller from selling drug j. As the left-hand side of Equation (3) approaches 0, the buyer gains on bargaining power. Alternatively, a value closer to 1 indicates increased bargaining power of the seller.

[17] We follow previous bargaining studies (cited earlier) and assume that the seller is not constrained in production and the seller's outside option is set to zero, that is, $d_{jct} = 0$.

[18] $\left(\frac{\partial q_{jct}}{\partial p_{jct}} \frac{p_{jct} - mc_j}{q_{jct}}\right) = -1$ implies the perfectly competitive environment where suppliers price at marginal cost, and $\left(\frac{\partial q_{jct}}{\partial p_{jct}} \frac{p_{jct} - mc_j}{q_{jct}}\right) = 0$ captures the Bertrand-Nash case where suppliers are price setters.

The relative bargaining power of buyers and sellers can be retrieved based on observables (p_{jct} and q_{jct}), the mc_j, and the partial derivative of quantity with respect to price ($\frac{\partial q_{jct}}{\partial p_{jct}}$), which will be estimated on the demand side. Since the marginal costs and the bargaining parameters are not separately identified, we estimate the bargaining parameters while adopting assumptions on the marginal costs that are based on findings from previous studies. Studies have shown that, for established generic drugs, marginal costs are close to price (see Berndt (2002), Grabowski and Vernon (1992), Scott Morton and Kyle (2012), Aitken et al. (2008), Berndt et al. (1996) etc.). For example, Berndt (2002) states that many small molecule drugs have variable and marginal costs that are "measured in nickels and dimes, not dollars" and, moreover, generic firms are unlikely to engage in marketing a specific drug so marginal costs should be similar across firms for the same generic drug. However, despite prices being close to marginal cost, there is still generally a positive profit margin in this industry (Berndt (2002), Reiffen and Ward (2005)). Reiffen and Ward (2005) estimate this positive profit margin to be 20-30% for the first generic entrant, tending toward 0 after ten competitors. Building on these results and adopting those to the number of competitors in our markets, we assume a profit margin of at least 12-13%, which translates into a drug-specific marginal cost that is at most 89% of the lowest transaction price of this drug. The marginal cost is adjusted by geographic regions in order to account for potential differences in transportation costs.[19] This marginal cost assumption is consistent with previous studies that have shown that marginal cost for generic pharmaceuticals is low and has little effect on a firm's pricing strategy (Dunn (2012)). We also conducted several robustness checks that further changes the marginal costs relation to the lowest transaction price. In one check we set marginal cost to 80% of the lowest transaction price and in another we set marginal cost to 100% of the lowest transaction price. The results show less than a 1% difference in the overall bargaining power distribution.[20]

Finally, we note that the surplus of the buyer (π_{ct}) associated with a set of alternative drugs J_{ct} takes a closed form solution (while assuming an *iid* extreme value type 1 distribution on the error term (ϵ_{ijct}) that enters the indirect utility function, as will be explained later):

$$E(\pi_{ct}(p_{jct})) = \frac{1}{\alpha_i} E\left[\underset{j \in J_{ct}}{max} \left(d_{cjt} + \epsilon_{ijct}\right)\right]$$

[19] We distinguish between five regions in Brazil: North, Northeast, Center-West, Southeast, and South.
[20] See Table 18 and Table 19 as well as Figure 4 through Figure 7 in Appendix B.

$$= \frac{1}{\alpha_i} \ln \left(\sum_{j \in J_{ct}} \exp(d_{jct}) \right) + K, \tag{4}$$

where α_i is the disutility of price, which will be estimated in the demand equation, and K is a constant. Note, that Equation (4) is useful to obtain two parts. The expected surplus for the whole choice set J_{ct} (i.e., $E(\pi_{ct}(p_{jct}))$, the left-hand side of Equation (4)), and the surplus for the choice set $J_{ct} \backslash \{j\}$ (i.e., $E(\pi_{ct}(p_{jct}; J_{ct} \backslash \{j\}))$, where good j is excluded from the choice set (see also Train (2009)).

3.2 Demand

In order to estimate bargaining parameters, we need estimates for the partial derivatives ($\frac{\partial q_{jct}}{\partial p_{jct}}$), which are derived from the price elasticities. Moreover, we need the surplus of the buyer (π_{ct}), which depends on the disutility of price (α_i) (see Equation (4)) that is estimated in the demand equation.

On the demand side, we assume that physicians choose the drug prescriptions for patients, accounting for their own, as well as hospital, city, and patient preferences. Drugs are chosen from a set of drugs in a specific drug class, city, and period. The alternative treatment encompasses patients' opportunities to consider alternative drugs or treatments beyond the ones considered in the specific drug classes. We follow Bokhari et al. (2018) and formulate a buyer's outside option as a residual category of drugs that is not considered in the specific drug class under consideration. This residual category is any other drug in the dataset.

In order to describe a patient's drug choice, we use a random utility model that allows for a random coefficient.[21] The indirect utility is specified as follows:

$$u_{ijct} = \alpha_i p_{jct} + X_j \beta + \xi_{jct} + \epsilon_{ijct}. \tag{5}$$

The coefficient α_i captures patients' heterogeneity in the disutility of price, which is allowed to vary across patients (and drug classes). The flexibility of this coefficient avoids the strict constraints on the substitution patterns inherent in a standard multinomial logit. A set of time-invariant observed drug characteristics enters X_j, and β is a parameter of interest. We also allow

[21] Other empirical studies that estimate demand based on a random utility model are Dunn (2012), Duso et al. (2014), Björnerstedt and Verboven (2016), Bokhari et al. (2017), and Bokhari et al. (2018).

for unobserved (by the researcher) drug characteristics (ξ_{jct}), which capture unobserved drug-, city-, and period-specific advertising campaigns, product safety warnings, etc. The mean utility of the alternative treatment is normalized to zero. Finally, ϵ_{ijct} is an idiosyncratic error term that is assumed to be *iid* and extreme value type 1 distributed.

3.2.1 Estimation of Demand Parameters

The heterogeneous parameter, α_i, from Equation (5) is dependent on patient characteristics, such as average income, employment rate, age, prevalence of heart disease, etc. Since these characteristics are unobserved in our setting, we model these as:

$$\alpha_i = \alpha + \Sigma\nu_i, \quad \nu_i \sim N(0, I), \tag{6}$$

where α is the mean disutility of price common to all patients and ν_i are the unobserved patient-specific characteristics that affect drug price sensitivity. We assume ν_i follows a standard normal distribution.

We can define the mean utility, which is common to all buyers, as:

$$\delta_{jct} = \alpha p_{jct} + X_j\beta + \xi_{jct}. \tag{7}$$

Let the vector $\theta = (\theta_1, \theta_2)$ be a vector containing all unknown parameters of the model, where $\theta_1 = (\alpha, \beta)$ contains the linear parameters and $\theta_2 = \Sigma$ contains the nonlinear parameters. We can now express the indirect utility as:

$$u_{ijct} = \alpha_i + \delta_{jct} + \mu_{ijct} + \epsilon_{ijct} \tag{8}$$

where

$$\mu_{ijct} = \mu(p_{jct}, \nu_i; \theta_2) = p_{jct}\Sigma\nu_i.$$

Utility is composed of the mean utility common to all consumers and the $\mu_{ijct} + \epsilon_{ijct}$ term, which represents a mean-zero heteroskedastic deviation from the mean utility. It captures the heterogeneity with respect to disutility of price across consumers.

Next, we consider a set A_{jct} of unobserved characteristics of patients who choose drug j in city c and period t:

$$A_{jct} = \{(\nu_i, \epsilon_{ijct}) | U_{ijct} \geq U_{ikct}\}. \tag{9}$$

The market share of product j in market ct can be written as the integral over the mass of buyers that choose drug j:

$$s_{jct} = \int_{A_{jct}} dF(\nu, \epsilon) = \int_{A_{jct}} dF_\nu(\nu) dF_\epsilon(\epsilon). \tag{10}$$

if we assume that the two random variables for a given patient are independently distributed. Using the assumptions on ϵ_{ijct}, the probability that an individual will choose drug j in market ct, is:

$$s_{ijct} = \int_{A_{jct}} \frac{exp(\delta_{jct} + \mu_{ijct})}{\sum_{j=0}^{J} exp(\delta_{jct} + \mu_{ijct})} dF_\nu(\nu). \tag{11}$$

This integral has no simple analytical solution and, therefore, needs to be approximated by taking simulation draws for the unobserved patient heterogeneity. To obtain the model predicted shares, we generate $N = 400$ random draws from $F_\nu(\nu)$. Denoting n as a random draw for ν_i, we can calculate the predicted market shares as:

$$\hat{s}_{jct} = \int_{A_{jct}} s_{ijct} dF_\nu(\nu) = \frac{1}{N} \sum_{i=1}^{N} s_{icjt} = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{exp(\delta_{jct} + \mu_{ijct})}{\sum_{l=0}^{J} exp(\delta_{lct} + \mu_{ilct})} \right). \tag{12}$$

We estimate this model using GMM in which we search over a set of parameter values to match the theoretical market shares with the observed market shares using the contraction mapping introduced by Berry, Levinsohn, and Pakes (1995).[22]

Based on the estimates, we can calculate the own-price elasticity of demand (η_{jjct}) for drug j in market ct. The own-price elasticity can be calculated as follows:

$$\eta_{jjct} = \frac{\partial s_{jct}}{\partial p_{jct}} \frac{p_{jct}}{s_{jct}} = \frac{-p_{jct}}{s_{jct}} \int_{A_{jct}} \alpha_i s_{ijct} (1 - s_{ijct}) dF_\nu(\nu). \tag{13}$$

This own-price elasticity is then used to get an estimate of the partial derivative, $\frac{\partial q_{jct}}{\partial p_{jct}}$, which is used in Equation (3) to back out the bargaining power.

[22] We implement this algorithm using the code developed by Vincent (2015).

4 Results

4.1 Demand Parameters and Elasticities

We estimate demand separately for each drug class. The demand parameters measure the distribution of preferences for drugs in each drug class across cities and time periods.

One problem with the estimation of the model is the correlation of price with the error term. Various unobserved, drug-specific characteristics such as advertising campaigns and product safety warnings can influence the price such that the error term is potentially correlated with the drug price. We treat price as an endogenous variable and use two instruments for the drug price, p_{jct}.

First, we use the average price of all drugs in the same drug class in city c and period t with the exception of drug j. As drug j and other drugs in that drug class are at least imperfect substitutes, their prices should be correlated.

We also use a second instrument that is often referred to as a "Hausman" type of instrument (see Hausman (1996) and Nevo (2000)). Identification using such an instrument relies on the correlation between prices across geographic markets due to common cost shocks rather than common demand shifters. In our case, the price of drug j across cities is assumed to be uncorrelated across demand, but correlated across common marginal cost components. Therefore, the average price of a certain drug from other geographic markets serves as an instrument for the price of the same drug in a specific market and time period. A joint F-test of these instruments gives an F-statistic of 2,070 which provides support that these are strong instruments.

Table 2 presents the estimated means and standard deviations for the price coefficient, α, and the estimates of the β coefficients of drug characteristics. These estimates are presented for each of the five drug classes.

The mean α coefficients are negative and significant for all drug classes, indicating that higher prices are associated with lower utility. The standard deviations of α are statistically significant for three of the five drug classes. In these drug classes, patients differ from each other in how sensitive they are to price.

The estimates on the β coefficients measure the effects of three drug characteristics: half-life, indications, and contraindications.[23] Half-life measures how quickly a drug begins to become

[23]We also controlled for different tables sizes which do not have a significant effect. This result confirms that

effective once taken. The estimate on the coefficient changes signs, and it is significant in three of the five drug classes. The positive estimates on the coefficients for the number of indications reflect that the number of conditions a drug is able to treat increases utility. The negative estimates on the coefficients for the number of contraindications show that a larger number of conditions in which a drug should not be used is generally associated with lower utility (note that there are exceptions in one drug class for each of the three coefficient estimates on the drug characteristics variables).

Table 2 also reports the own-price elasticities across drug classes.[24] Own-price elasticity estimates vary across drug classes and take on values from -1 to 0 (see Table 2). The own-price elasticities appear to be small due to the fact that we estimate the elasticities along the individual demand curve due to the detailed information on specific transactions and negotiations that we use. Hence, these price elasticities are measured along individual demand curves which, by definition, are more inelastic than the price elasticities evaluated along the market demand functions (as defined by the sum of individually demanded quantities). Moreover, associated transaction costs with bargaining frequently results in large transaction volumes purchased for low prices, which leads to low price elasticities.

Our price elasticities are also comparable to drug-specific elasticities reported in other studies. For example, Einav et al. (2018) find an average drug-specific price elasticity of -0.23 for 150 drugs. In a similar vein, Grennan (2013) finds small own-price elasticities that average -0.4. He mentions that small elasticities are consistent with two qualitative facts in his setting: (1) doctors are not very price sensitive, and (2) prices are negotiated. The small elasticity estimates show that price does matter in treatment choice, but relatively little. This is also consistent with the limited evidence from previous studies that suggest physicians and hospitals are relatively insensitive to financial incentives. Gaynor et al. (2004) find health maintenance organizations are able to reduce costs by only 5% through physician incentive programs. Other studies have found physician prescription behavior to be generally insensitive to price (Dafny (2005) and Carrera et al. (2018)). Gruber (2001) finds the elasticity of insurance coverage is -0.6. Finally, small

tablets of specific sizes do not have a significant effect on demand and no significant power to explain the price variations.

[24]The reported elasticities are averaged across individual drugs within a class, cities, and time periods. The own-price elasticities for single drugs, as well as the cross-price elasticities of those drugs, are reported in Appendix A.

elasticities go hand in hand with bargaining because prices are, by construction, lower than a price-setting supplier would set to a price-taking buyer. As a result, small elasticities could reflect low buyer price sensitivity, low supplier bargaining ability, or a combination of both (Grennan (2013)). We also estimate the own-price elasticities in a reduced form way by regressing the log of quantity on the instrumented log of price and other determinants. This gives similar own-price elasticities for three of the five classes. The results of this estimation are presented in Table 20 in Appendix B.

The reported cross-price elasticities (see Appendix A) are consistent with drugs within a class being substitutes rather than complements (except the "other" class). With the exception of bisoprolol and metoprolol (both beta blockers), all cross-price elasticities are positive, indicating that molecules within drug classes tend to be substitutes. This is further supported by the cross-price elasticities in the "other" drug class being near zero. Unlike the other drug classes, these drugs are not medically related to one another. Thus, it is less likely they would be medically substitutable for each other.

Recall that the estimates of α, β, and own-price elasticity serve to calculate the expected surplus a buyer receives from purchasing a drug, as shown in Equation (4). The surplus calculation is then used to evaluate the difference $(\pi_{ct} - d_{jct})$, as shown in Equation (3), which then enables us to calculate the relative bargaining power ratio as shown on the left-hand side of Equation (3). Note that while elasticities and surplus measures are calculated within a time period, prices and quantities are transaction-specific. Thus, a bargaining power ratio is calculated for every individual transaction. With this in mind, we next explore the degree of heterogeneity between buyer and seller bargaining abilities.

4.2 Heterogeneity of Bargaining Ability

Table 3 reports the summary statistics on the estimated bargaining power ratios overall and across drug classes. Due to the construction of the bargaining power ratio (see Equation 3), the bargaining power surplus is reported as the percentage of surplus received by the seller. Remember, smaller bargaining power ratios indicates more bargaining power surplus for the buyer, while larger bargain power ratios indicate more bargaining power for the seller. Beginning with the overall bargaining power across all drug classes, the seller received 44.8% of the bargaining

surplus, on average. The buyer received the remainder, 55.2%, of the bargaining surplus across all drugs. Although this is close to an even split between the buyer and seller, a larger mean compared to the median indicates that the distribution is skewed to the right (buyers tend to do better more often). The high standard deviation indicates that there is substantial heterogeneity in bargaining outcomes across buyers. Figure 1 illustrates the overall bargaining power ratio for every transaction across all drug classes. It shows an even surplus split is an unlikely outcome for any given transaction, as the bargaining power distribution is bimodal.

Turning to the bargaining power ratios across drug classes, Table 3 shows that sellers achieve higher bargaining power for alpha blockers and other drug classes, about 67% and 73%, respectively. In contrast, buyers achieve higher bargaining power in the calcium channel blocker and diuretic classes, where they get about 73% and 62% of the surplus, respectively. In comparing these bargaining power estimates and relating those to the estimated elasticities, it is interesting to note that sellers achieve higher bargaining power in relatively more elastic markets, while buyers achieve more bargaining power in more inelastic markets. At first glance, this might appear counterintuitive, as one would expect to find buyers' bargaining power higher in more elastic markets. This result indicates that bargaining determinants, such as business relationships between buyers and sellers, become primarily important in explaining bargaining power and price variations.

Figure 2 illustrates large heterogeneities in bargaining power realizations across drug classes. The figures on the alpha blockers and other drug classes show a large mass on the upper end of the bargaining power distribution. The calcium channel blocker and diuretic classes are characterized by lower bargaining power realizations. The different bargaining power realizations, especially across different drug classes, raise the question of how prices will be affected by changes to the relative bargaining power of buyers and manufacturers.

4.3 The Importance of Bargaining Power for Price Variation

Next, we shift our focus to evaluating how differences in bargaining power affect price variation across different drug classes. In order to do so, we examine the value-added terms on the right-hand side of Equation (3), that is, $((1 + \frac{\partial q_{jct}}{\partial p_{jct}} \frac{p_{jct} - mc_j}{q_{jct}})(\pi_{ct} - d_{jct}) + p_{jct} - mc_j)$. These terms represent the additional surplus to the buyer from purchasing drug j and the additional profit

to the seller from selling drug j. To simplify the notation and be consistent with the previous literature, we call these value-added terms AV_{jct} and define the bargaining power ratio as $BP_{jct} = \frac{b_{jt}(c)}{b_{jt}(c)+b_{ct}(j)}$. Now, rearranging Equation (3) we get:

$$p_{jct} - mc_j = BP_{jct}AV_{jct}. \tag{14}$$

We separate the product of bargaining ability and the value-added terms by taking logarithms:

$$ln(p_{jct} - mc_j) = ln\left(BP_{jct}\right) + ln(AV_{jct}). \tag{15}$$

We use the variance of all of these terms to measure how differences in bargaining ability influence overall price variation. Comparing the variance in the bargaining power ratio to the total variance of both terms gives us the percentage of price variation that is originated by differences in bargaining ability.[25]

$$Price\ Variation\ due\ to\ bargaining = \frac{V\left(ln\left(BP_{jct}\right)\right)}{V\left(ln\left(BP_{jct}\right)\right) + V(ln(AV_{jct}))}. \tag{16}$$

Table 4 reports the price variation due to bargaining power. This variation ranges from about 40% to 56% across the different drug classes and 42.9% overall. This means that differences in bargaining ability are able to explain 42.9% of the overall price variation (the rest is explained by other demand and supply factors).

Figure 3 illustrates the different outcomes of bargaining strength across drug classes. The figure illustrates that changes in bargaining power have very different effects on prices.[26] While an improvement in bargaining power can have strong price-reducing effects in the calcium channel blocker and diuretic classes, it has only small effects in the other drug classes. Therefore, if buyers are interested in achieving stronger price-reducing effects, it would be wise to strengthen their position in these drug classes. This raises the question: How do buyers strengthen their bargaining power in these drug classes? Next, we focus on the determinants of bargaining power and evaluate improvements in various bargaining determinants on bargaining power and prices across drug classes.

[25] See Grennan (2014), Section 5.1

[26] Figure 3 will be explained in more detail in a later section of the paper.

4.4 Determinants of Bargaining Ability

Since bargaining power accounts for a significant amount of price variation and buyers face different prices, it must be the case that bargaining power differs across buyers and sellers. However, it is unclear whether these differences in bargaining power are due to an individual negotiator's ability or if there are systematic characteristics of buyers, sellers, or markets that can explain differences in bargaining power. There might be specific characteristics of buyers or sellers associated with higher bargaining power. However, there might also be differences in bargaining power over time. For instance, buyers or sellers might learn about the negotiation process and get better at bargaining over time. There could also be business relationships between buyers and sellers that develop over time and influence the relative bargaining power.

To explain how different characteristics affect bargaining power, we examine different categories of bargaining power determinants. These categories include quantity, buyer-seller business relationships, learning and time trends, and market structure. Additionally, we include variables to control for an individual buyer's idiosyncratic bargaining ability. We estimate the following regression:

$$\begin{aligned} ln(BP_{jct}) = & \underbrace{\beta_1 ln(q_{jct})}_{\text{Quantity}} \\ & \underbrace{+\beta_2 Loyalty_{cjt} + \beta_3 Multiple\ Drug\ Purchases_c + \beta_4 Renegotiation_{jct}}_{\text{Business Relationships}} \\ & \underbrace{+\beta_5 Cumulative\ Transactions_{ct} + \beta_6 Period_t}_{\text{Learning and Time Trend}} \\ & \underbrace{+\beta_7 Population_c + \beta_8 Number\ of\ Hospitals_c + \beta_9 Number\ of\ Sellers_c}_{\text{Market Structure}} \\ & \underbrace{+\beta_{10} Average\ ln(BP)_{-class,c} + \beta_{11} Average\ ln(BP)_{-drug,c}}_{\text{Bargaining Power Fixed Effect}} + \epsilon_{jct}. \end{aligned} \tag{17}$$

The dependent variable, BP, is the bargaining power ratio, as previously defined. Table 5 shows summary statistics for the independent variables in Equation (17).

The variable q measures the quantity (in total number of doses) that a buyer purchases in each transaction. Buyers have the option to engage in a large transaction with the aim of obtaining a quantity discount. Alternatively, a buyer can engage in multiple negotiations and

smaller transactions in a hope of achieving better price offers. *A priori*, the sign on the quantity coefficient is undetermined and depends on which motivation is the dominating force.

The second set of variables in Equation (17) describes the business relationship between buyers and sellers. These variables measure whether specific types of business relationships exert an effect on bargaining power. The first variable, *Loyalty*, measures the percentage of transactions for a specific drug that a buyer makes with the same seller relative to the total number of transactions for this drug in a month. For example, if a buyer makes five total purchases of a drug and four of the five purchases are from a single seller, then the buyer's loyalty value would be 0.8. In contrast, if the five purchases were from five different sellers the loyalty value would be 0.2.[27] The mean and median values of this variable are around 0.67, indicating that the median buyer makes about two-thirds of its purchases from sellers it has purchased from before.

The next relationship variable, *Multiple Drug Purchases*, measures the total number of *different* drugs that a buyer has purchased from a single seller. For example, if a buyer purchased atenolol, metoprolol, and diltiazem from one seller, the *Multiple Drug Purchases* measure takes on a value of 3 since it has purchased three different drugs. A high measure indicates a close business relationship between buyer and seller and presumably may strengthen buyer power.

The variable *Renegotiation* measures how many times a given buyer purchases a certain drug in a single month, conditional on them purchasing that drug at least once. For example, if a buyer made one purchase of atenolol in January 2015, then their renegotiation value would be 1. If the buyer made two purchases of atenolol in a month, the value would be 2, etc. Both the median and average values of this variable are around 2, indicating that buyers often make two purchases of a drug in a month. Renegotiations could be measuring a buyer's failure to accurately predict the demand for a certain drug. In this case, we would expect to see a higher value of this variable associated with a lower buyer bargaining power. Renegotiations could also be representative of buyers' permanent searches for better offers. Buyers may engage in multiple consecutive transactions aiming to increase their buyer bargaining power and purchase drugs for lower prices.

We consider that learning via experience may improve bargaining power, and we establish a variable, *Cumulative Transactions*, that measures the cumulative transactions for each buyer

[27]Note that a buyer has to make at least two purchases of a drug for this variable to be defined. If a buyer makes only a single purchase of a drug, we refer to this as a non-existent relationship, and the observation is dropped.

over time. For example, if a buyer completes two transactions in month one, their cumulative transaction value is 2. If they complete an additional two transactions in month two, their cumulative transaction value is 4, etc.[28] If buyers learn to negotiate better over time, we expect a negative coefficient.

In order to control for any remaining systematic changes in bargaining power over time, we establish a time trend that assigns a counter to the time when a transaction occurred. January 2015 would be month 1, while January 2016 would be month 13, etc.

The market structure variables measure the size of the buyer and the degree of competition in a market. Buyer size is measured by the variable *Population*, which counts the number of inhabitants in the market.

The variable *Number of Hospitals* measures the total number of health establishments in a city. The city buyer negotiates on behalf of all health establishments, which may have several implications for bargaining power. First, the city needs to anticipate the expected drug demand of each individual hospital, and they may make incorrect predictions. Second, the drugs need to be distributed across hospitals, which is burdensome and may constitute a transaction cost.

The variable *Number of Sellers* measures the total number of unique drug manufacturers that operate in the market. This variable measure competition in a market. The median market consists of 11 unique sellers.

We add two additional variables that control for buyer-specific bargaining ability as a fixed effect. The idea is to control for buyer-specific bargaining performance that could depend on organizational features, skills, or other factors that are unobserved. The first variable, $AverageBP_{-class,c}$, measures the average bargaining power of the buyer across all other drug classes except the one under consideration. For example, if a buyer is a strong negotiator in other drug classes, we would expect the buyer to achieve good bargaining performance in the considered drug class. Similarly, the variable $AverageBP_{-drug,c}$ measures the average bargaining power of a buyer in all other drugs within the drug class under consideration. It captures correlation of bargaining skills across drugs within a drug class.

The regression results of Equation (17) are shown in Table 6. Due to the construction of the bargaining power variable (see Equation (3)), a negative regression coefficient on an explanatory

[28] Table 5 reports that an average buyer has completed 36 transactions throughout the time period.

variable is associated with more buyer bargaining power, while a positive coefficient is associated with more seller bargaining power. The regression results show that a higher transaction quantity increases buyer bargaining power. This estimate is significant and consistently negative across all drug classes. Hence, a larger quantity of doses purchased in a transaction increases buyer bargaining power. This result is consistent with previous studies that refer to large orders resulting in discounts (Grennan (2014), for example).

We turn to the estimation results of the business relationship variables, that is, *Loyalty*, *Multiple Drug Purchases*, and *Renegotiation*. The coefficient on the *Loyalty* variable is statistically significant and negative in four of the five drug classes (but not overall). The result shows that higher drug purchases concentrated on the same seller are associated with higher buyer bargaining power.

The coefficient on the *Multiple Drug Purchases* variable is significant and negative in the majority of the drug classes. This result provides evidence that a larger drug variety purchased from the same seller is associated with higher buyer bargaining power.

The regression results for the *Renegotiations* variable turns out to be significant and positive in the majority of the drug classes. Hence, renegotiations frequently result in a loss of the buyer's bargaining power. This result shows that buyers find it difficult to achieve better deals while committing to multiple (and possibly smaller) transactions. The result could also be interpreted as buyers facing a shortage that could be caused by a positive shock in demand or poor evaluation of expected demand.

To summarize, our business relationship variables turn out to have high explanatory power. Closer business relationships in the form of loyalty and larger product variety or larger drug portfolios improve buyers' bargaining power. In contrast, renegotiations frequently reduce buyers' bargaining power. The question as to what extent these relationship variables eventually affect prices certainly arises; our analysis focuses on this question in the next section.

The estimate on the variable *Cumulative Transactions* is not consistently significant nor consistently associated with either buyer or seller bargaining power. Moreover, the magnitude of the effect is rather small. This result provides evidence that buyer learning over time is not a strong explanatory factor. The time trend, as measured by *Period*, is significant for each drug class but changes signs across drug classes. This result shows that time-varying changes are associated with

improvements in both buyer and seller bargaining power. Our study suggests learning could improve buyer or seller bargaining power, while business relationship has strong explanatory power on buyer bargaining power. This result provides further insights to related studies that show that buyers perform better over time, primarily due to learning (see, for example, Grennan (2014)).

Turning to the market structure variables, we find that a larger buyer, measured by *Population*, is associated with higher buyer bargaining power in four of the five drug classes, but it is statistically significant in only one drug class. A larger *Number of Hospitals* in a city generally reduces buyer bargaining power. This could be indicative of coordination or transaction challenges. It could become more difficult for a city with many hospitals to accurately predict demand or to distribute drugs to hospitals. Since demand prediction is more difficult, buyers might need to purchase smaller quantities of drugs on shorter notice in order to meet unforeseen demand. This could reduce their bargaining power.

A further increase in seller competition, measured by the *Number of Sellers*, increases buyer bargaining power in most of the drug classes. This result is expected, as when there are more sellers, there are more choices for buyers; this, in turn, may improve their negotiation position with any one seller.

Finally, the estimates on the buyer fixed effects ($AverageBP_{-class,c}$ and $AverageBP_{-drug,c}$) are positive and significant in most cases. The positive coefficient indicates that higher buyer bargaining power correlates across drug classes and drugs within classes. This finding is particularly interesting, as it suggests that firms' bargaining power appears to showcase a level of consistency that is independent of negotiations pertaining to any particular drug or drug class.

4.5 The Effect of Bargaining Power Determinants on Price

While our estimation results, as shown in Table 6, provide good insights into the correlation between bargaining determinants and bargaining power, we would like to get more insight into the impacts on prices. Therefore, we now evaluate how the changes in bargaining power (caused by change in the bargaining determinants, business relationship, learning and time trends, and market structure characteristics, see Table 6) translate into price changes.

We can evaluate the price effect with respect to changes in bargaining power based on Equation

(2):

$$p_{jct} = \frac{mc_j + BP_{jct}\left[\left(1 + \frac{\partial q_{jct}}{\partial p_{jct}}\frac{p_{jct}-mc_j}{q_{jct}}\right)\left(\pi_{ct}(p) - d_{jct}\right) - mc_j\right]}{1 - BP_{jct}} \tag{18}$$

This equation allows us to iteratively solve for new equilibrium prices given any considered changes in bargaining power (BP_{jct}), while keeping other variables at their means.

We begin with illustrating the relationship between bargaining power and prices for each drug class, as shown in Figure 3. The points on each function show the estimated bargaining power parameter in every drug class. The functions in this figure illustrate nicely that changes in bargaining power have different effects on prices across drug classes, since this relationship is determined by marginal costs, price elasticities, and surplus measures that are specific to drug classes. Hence, the steepness of functions to the left and right of the marked points (our estimated bargaining power) illustrate to what extent an improvement in buyer and seller bargaining power will decrease or increase prices, respectively. More specifically, we observe that improvement in buyer bargaining power (movements to the left of the point illustrated in the figure) can result in larger price reductions in the calcium channel blocker and diuretic drug classes than in the other drug classes.

Turning to the relationship between bargaining determinants, bargaining power, and prices, we build on the estimation results as reported in Table 6. Using Equation (18) and the regression results, we evaluate the effect of a 10% increase in a bargaining determinant on price.[29] Table 7 shows the percentage change in price that occurs with a change in a bargaining determinant and bargaining power.

As shown, a change in transaction quantity has a strong effect on price. A 10% increase in transaction quantity reduces the bargained price by 6.15% due to stronger buyer bargaining power. The magnitude of this effect is consistent across each drug class.

The business relationship determinants also exert strong effects on prices. Increases in *Loyalty* and *Multiple Drug Purchases* by 10% result in 2% and 4% lower prices, respectively, in the overall data. However, for each individual drug class the effect is usually much stronger. In contrast, a 10% increase in the number of *Renegotiations* results in lower buyer bargaining power and an over 13% increase in prices, the highest change among all determinants, though the direction of the price change is not always consistent across all classes.

[29] In the case of the period variable, we use an increase of one month rather than 10%.

Turning to the learning determinant, an increase in *Cumulative Transactions* causes a price increase of almost 4%. The time trend variable reduces prices by 1.3% each month.

The market structure variable, *Population*, has little effect on prices. A 10% increase in buyer or market size decreases price by only half of a percent, after controlling for the quantity purchased. A market structure variable that describes a larger price effect is *Number of Hospitals*. Here, a 10% increase in that number of hospitals increases prices by 5.65%. A 10% increase in the number of sellers decreases price by only 1.4% overall, but the effect of this determinant can be much stronger in most drug classes. In all classes except Diuretics a 10% increase in the number of sellers can result in a large price reduction. Since each market in our dataset has at least several competitors, we cannot claim this same result will hold when moving from only one or two competitors to several.

To summarize, we recognize that increases in buyer bargaining power can exert different effects on prices, as shown in Figure 3. We also recognize that specific bargaining determinants—such as transaction size, *Quantity*, and the business relationship variables, *Loyalty*, *Multiple Drug Purchases*, and *Renegotiation*—have large effects on buyer bargaining power and can lead to significant price changes. For these reasons, we argue that transaction quantity and business relationships are important to improve buyer bargaining power and to achieve price reductions. Firm fixed effects, as measured by bargaining abilities, seem to be impactful as well. Bargaining power improvement over time via learning has a rather minor effect on bargaining power and prices.

5 Conclusion

This study examined the price variation in the pharmaceutical drug market. Making novel use of a database, we are able to retrieve information on bargaining outcomes, such as, single transaction prices, quantities, buyers, and sellers for a variety of drugs. The data descriptives show a large degree of drug price variation across bargaining transactions, where the variation across buyers exceeds the variation over time.

The estimation results of a structural model provide evidence that buyers with closer business relationships, measured by exclusive drug purchases made from the same seller and larger drug portfolios purchased from the same seller, achieve higher bargaining power and lower drug prices.

Renegotiations frequently reduce buyer bargaining power and increase drug prices. So, buyers that purchase the same drug more often generally do worse than buyers that purchase less often, controlling for transaction volume. Together, these business relationship variables suggest that buyers who form stable and consistent relationships with a small number of suppliers tend to have stronger relative bargaining power.

To summarize, we recognized that increases in buyer bargaining power can exert different effects on prices, as shown in Figure 3. We also recognize that specific bargaining determinants—such as transaction size *Quantity* and the business relationship variables *Loyalty*, *Multiple Drug Purchases*, *Renegotiation*—have large effects on buyer bargaining power and can lead to significant price reductions. For these reasons, we argue that transaction quantity and business relationships are important to improve buyer bargaining power and to achieve price reductions. Firm fixed effects, as measured by average bargaining abilities in other products, seem to be impactful as well, suggesting that bargaining power is consistent both within and across drug classes. This finding lends support toward the notion that bargaining ability has a level of stability such that high ability firms will tend to consistently do better than low ability firms when negotiating prices with buyers. Finally, we find that bargaining power improvements over time via learning have a rather minor effect on bargaining power and prices.

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Tables and Figures

Table 1: Drug and Price Summary Statistics and Variation

Class/Drug	**Mean**	**Median**	**SD**	**Min**	**Max**	$\boldsymbol{PV_{buyer}}$	$\boldsymbol{PV_{time}}$
Doxazosin	0.238	0.072	0.363	0.035	3.800	1.014	0.528
Pentoxifylline	0.229	0.168	0.165	0.128	1.325	0.300	0.100
Tamsulosin	1.321	1.260	0.472	0.200	3.300	0.200	0.140
Alpha Blockers	0.348	0.175	0.472	0.035	3.800	0.577	0.390
Atenolol	0.037	0.023	0.043	0.0002	0.467	0.923	0.602
Bisoprolol	0.259	0.196	0.220	0.046	1.490	0.727	0.392
Carvedilol	0.056	0.028	0.088	0.0001	0.960	1.297	0.844
Metoprolol	0.307	0.249	0.272	0.033	1.840	0.788	0.643
Propranolol	0.010	0.005	0.024	0.0001	0.375	1.004	0.157
Beta Blockers	0.087	0.027	0.160	0.0001	1.840	0.959	0.641
Amlodipine	0.102	0.050	0.220	0.0006	3.590	1.220	0.557
Diltiazem	0.027	0.027	0.149	0.006	0.098	0.498	0.250
Nifedipine	0.143	0.027	0.683	0.0004	7.513	1.517	0.457
Nimodipine	0.073	0.010	0.591	0.003	7.332	0.984	0.140
Verapamil	0.029	0.020	0.038	0.012	0.260	0.531	0.073
CCBs	0.096	0.027	0.435	0.0004	7.513	0.961	0.406
Chlortalidone	0.125	0.075	0.128	0.025	0.840	0.690	0.316
Hydrochlorothiazide	0.046	0.030	0.045	0.0003	0.380	0.860	0.272
Indapamide	0.235	0.180	0.213	0.054	1.109	0.518	0.251
Spironolactone	0.155	0.067	0.192	0.001	1.067	1.201	0.777
Diuretics	0.120	0.055	0.163	0.0003	1.109	0.874	0.564
Clonidine	0.107	0.072	0.215	0.029	2.167	0.506	0.359
Hydralazine	0.177	0.093	0.431	0.010	3.850	0.791	0.425
Methyldopa	0.089	0.065	0.078	0.0003	0.385	0.874	0.603
Other	0.108	0.072	0.215	0.0003	3.850	0.719	0.507

Table 1 shows a list of all drugs in our dataset. Each section shows the price summary statistics for each drug and an average across all drugs in that class. The price variation (measured as a coefficient of variation) across buyers and across time is also presented.

Table 2: Demand Parameter Estimates

Coefficients	**Alpha Blockers**	**Beta Blockers**	**CCBs**	**Diuretics**	**Other**
Mean α	-1.060*	-1.973***	-0.759***	-0.726*	-2.174*
	(0.597)	(0.495)	(0.275)	(0.421)	(1.270)
SD α	0.552*	1.543***	0.002	0.246	1.464**
	(0.288)	(0.388)	(18.596)	(0.280)	(0.647)
Half-life	-0.226***	0.026	0.003	0.233***	-0.576***
	(0.085)	(0.018)	(0.005)	(0.016)	(.043)
Indications	1.527	-0.074***	0.709***	0.593***	0.452***
	(1.180)	(0.010)	(0.042)	(0.039)	(0.076)
Contraindications	-1.904**	-0.456***	-0.823***	1.705***	-1.692***
	(0.605)	(.029)	(0.062)	(0.155)	(0.100)
Own-price elasticity	-0.492	-0.115	-0.076	-0.094	-0.163

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2 presents the estimate for the disutility of price demand parameter, α, as well as the standard deviation of α. Also shown are estimates for β, the drug characteristics, for each drug class. Additionally, the average own-price demand elasticity is shown for each class.

Table 3: Seller Portion of Bargaining Power

Class	**Mean**	**Median**	**SD**	**Min**	**Max**
Total	0.448	0.389	0.318	0	1
Alpha Blockers	0.668	0.808	0.314	0.034	1
Beta Blockers	0.475	0.443	0.309	0	1
CCBs	0.268	0.190	0.229	0	1
Diuretics	0.379	0.318	0.306	0	1
Other	0.729	0.811	0.239	0.002	1

Table 3 presents bargaining power surplus summary statistics. Mean and median values closer to 0 indicate more buyer bargaining power, while values closer to 1 indicate more seller bargaining power.

Table 4: Price Variation from Bargaining Power

Class	**Price Variation from Bargaining (%)**	**Variation of Bargaining**	**Variation of Added Value Terms**
Alpha Blocker	52.8	0.598	0.533
Beta Blocker	52.1	1.202	1.106
CCBs	39.6	1.214	1.848
Diuretic	56.3	1.785	1.384
Other	41.5	0.528	0.744
Total	42.9	1.371	1.825

Table 4 presents the portion of price variation caused by differences in bargaining power. This is obtained from dividing the variation of bargaining power (column 2) by the total variation in price (the sum of columns 2 and 3).

Table 5: Summary Statistics of Variables in the Regression

Variable	**Category**	**Mean**	**Median**	**SD**	**Min**	**Max**
Quantity	Quantity	15,935	2,667	38,046	0.222	300,000
Loyalty	Business Relationship	0.693	0.667	0.283	0.032	1
Multiple Drug Purchases	Business Relationship	3.944	3	3.637	0	17
Renegotiation	Business Relationship	2.269	2	1.653	1	14
Cumulative Transactions	Learning	35.79	42	16.150	4	54
Period	Time Trend	10.936	12	6.454	1	24
Population (in millions)	Market Structure	0.033	0.012	0.096	0.001	1.538
Number of Hospitals	Market Structure	11.486	7	18.637	1	327
Number of Sellers	Market Structure	10.766	11	4.748	1	26

Table 5 shows the determinants of bargaining power and the categories of those variables in the regression (the bargaining power fixed effect variables are omitted in this table). The summary statistics of these bargaining power determinants are presented here.

Table 6: Determinants of Bargaining Power

Variable	**Alpha Blockers**	**Beta Blockers**	**CCBs**	**Diuretics**	**Other**	**Total**
ln(q)	-0.063***	-0.133***	-0.202***	-0.215***	-0.079***	-0.158***
	(0.019)	(0.009)	(0.012)	(0.017)	(0.015)	(.006)
Loyalty	-0.750***	-0.409***	-0.496***	-0.322***	-0.081	-0.051
	(0.149)	(0.068)	(0.103)	(0.123)	(0.096)	(0.042)
Multiple Drug Purchases	-0.013	-0.027***	-0.007	-0.032***	-0.021**	-0.018***
	(0.015)	(0.006)	(0.008)	(0.011)	(0.007)	(0.004)
Renegotiation	-0.009	0.036***	0.019	0.165***	-0.132***	0.069***
	(0.041)	(0.008)	(0.018)	(0.028)	(0.045)	(0.007)
Cumulative Transactions	0.0001	0.008***	0.003	-0.008***	0.013***	0.002
	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.001)
Period	0.025***	-0.014***	-0.014**	0.011**	-0.018***	-0.002
	(0.008)	(0.004)	(0.005)	(0.005)	(0.006)	(0.002)
Population	-0.041	0.293	-6.239***	-0.779	-0.037	-0.148
	(0.891)	(0.472)	(1.422)	(2.090)	(0.308)	(0.319)
Number of Hospitals	0.010**	-0.001	0.024***	0.014**	0.001	0.005***
	(0.005)	(0.003)	(0.005)	(0.006)	(0.002)	(0.002)
Number of Sellers	-0.008	-0.023***	-0.037***	0.022***	-0.030***	-0.002
	(0.012)	(0.005)	(0.007)	(0.008)	(0.009)	(0.004)
Average ln(BP), other classes	-0.015	0.815***	0.841***	1.266***	0.230	
	(0.310)	(0.162)	(0.243)	(0.241)	(0.200)	
Average ln(BP), other drugs	0.846***	0.454***	0.947***	-1.119***	1.043***	
	(0.132)	(0.111)	(0.195)	(0.140)	(0.231)	
R-sq	0.504	0.528	0.750	0.687	0.371	0.552
N	307	2,512	1,198	867	628	5,515

Table 6 presents the results from a regression of the log of bargaining power on variables relating to quantity, buyer-seller relationships (loyalty, multiple drug purchases, renegotiation), time (cumulative transactions, period), and market structure (population, number of hospitals, number of sellers), as well as a bargaining power fixed effect (average BP in other classes and average BP in other drugs).

Table 7: Change in Price Resulting from a Change in a Determinant
Percentage Change in Price if a Determinant Increases by 10%

Class	q	Loyalty	Multiple Drug Purchases	Renegotiation	Cumulative Transactions	Period (Increase of 1 month)	Population	Number of Hospitals	Number of Sellers
Total	-6.15	-1.99	-4.02	13.11	3.89	-1.31	-0.49	5.65	-1.40
Alpha Blockers	-5.98	-20.76	-6.23	-2.94	0.51	33.43	-0.41	23.63	-7.52
Beta Blockers	-6.00	-10.50	-6.14	6.39	26.18	-6.34	0.93	-0.88	-9.57
CCBs	-3.54	-5.39	-1.09	1.31	1.09	-2.55	-3.57	46.72	-6.07
Diuretics	-5.80	-5.97	-4.51	18.57	-4.95	80.53	-1.02	6.35	17.47
Other	-5.92	-4.45	-7.38	-16.06	44.02	-11.22	-0.15	15.23	-16.87

Table 7 presents the average change in price that would occur from a change in bargaining power when a certain bargaining determinant changes.

Figure 1: Overall Distribution of Bargaining Power

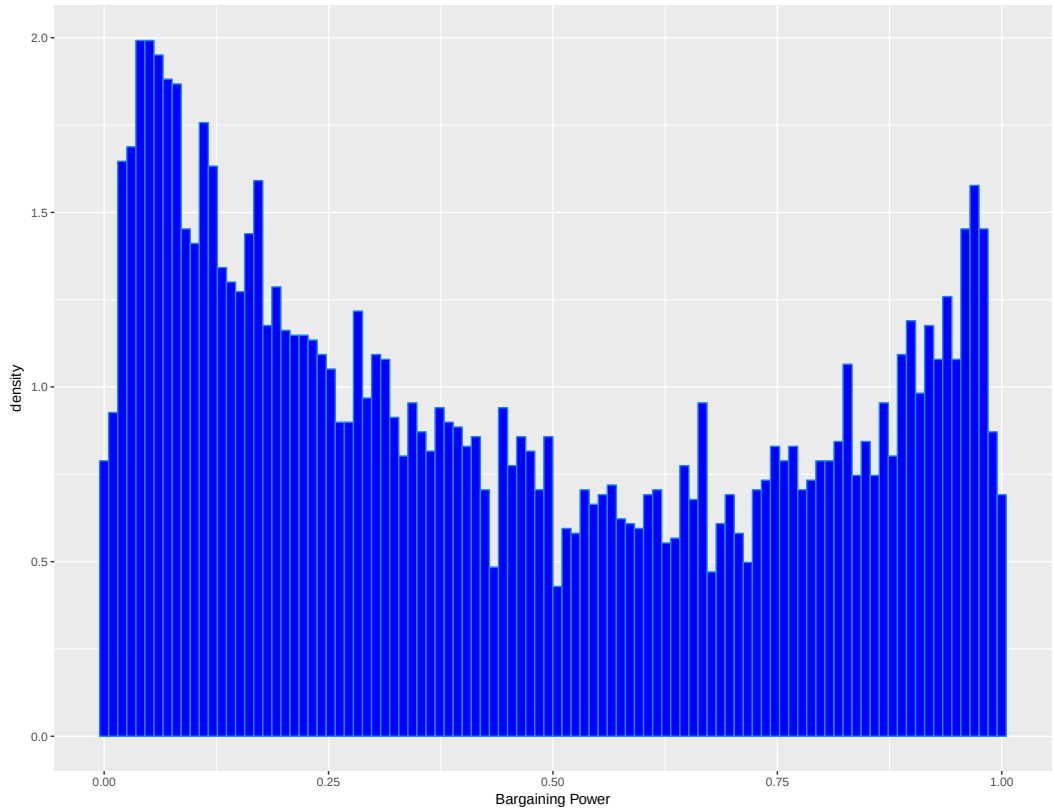

Figure 1 shows the overall distribution of bargaining power. Realizations close to 0 indicate high buyer bargaining power, and realizations close to 1 indicate high seller bargaining power.

Figure 2: Bargaining Power Distribution Across Drug Classes

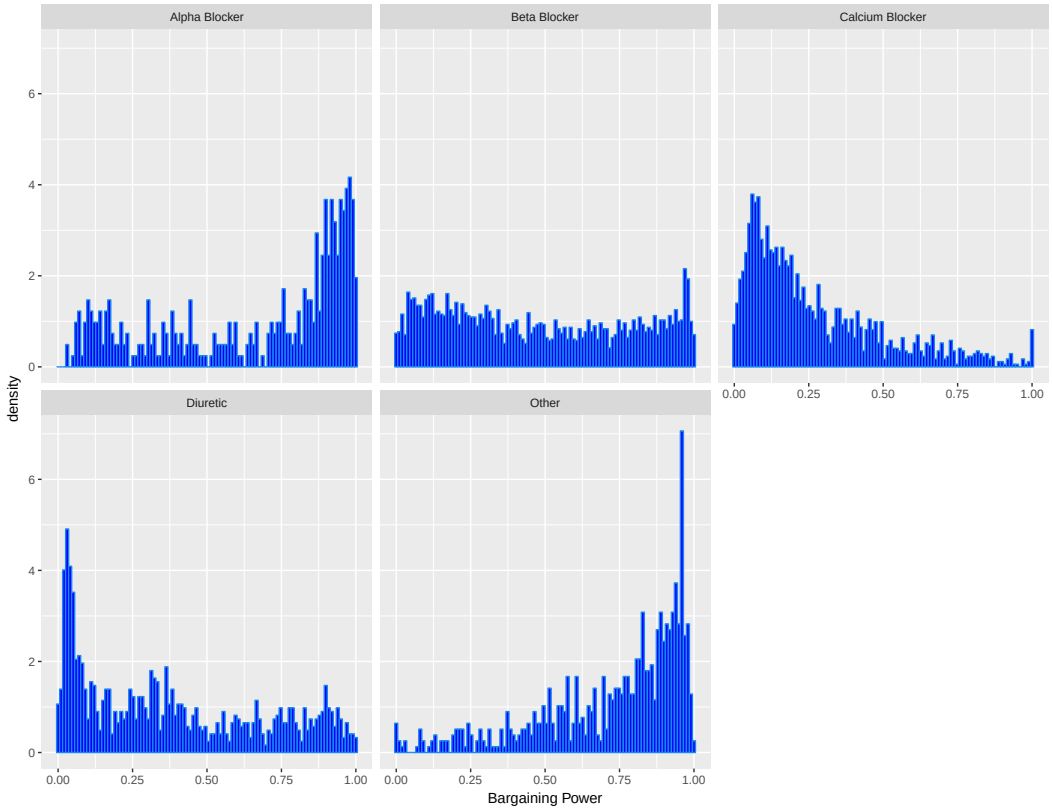

Figure 2 shows the distribution of bargaining power by drug class. Realizations close to 0 indicate high buyer bargaining power, and realizations close to 1 indicate high seller bargaining power.

Figure 3: Price vs Bargaining Power for each Drug Class

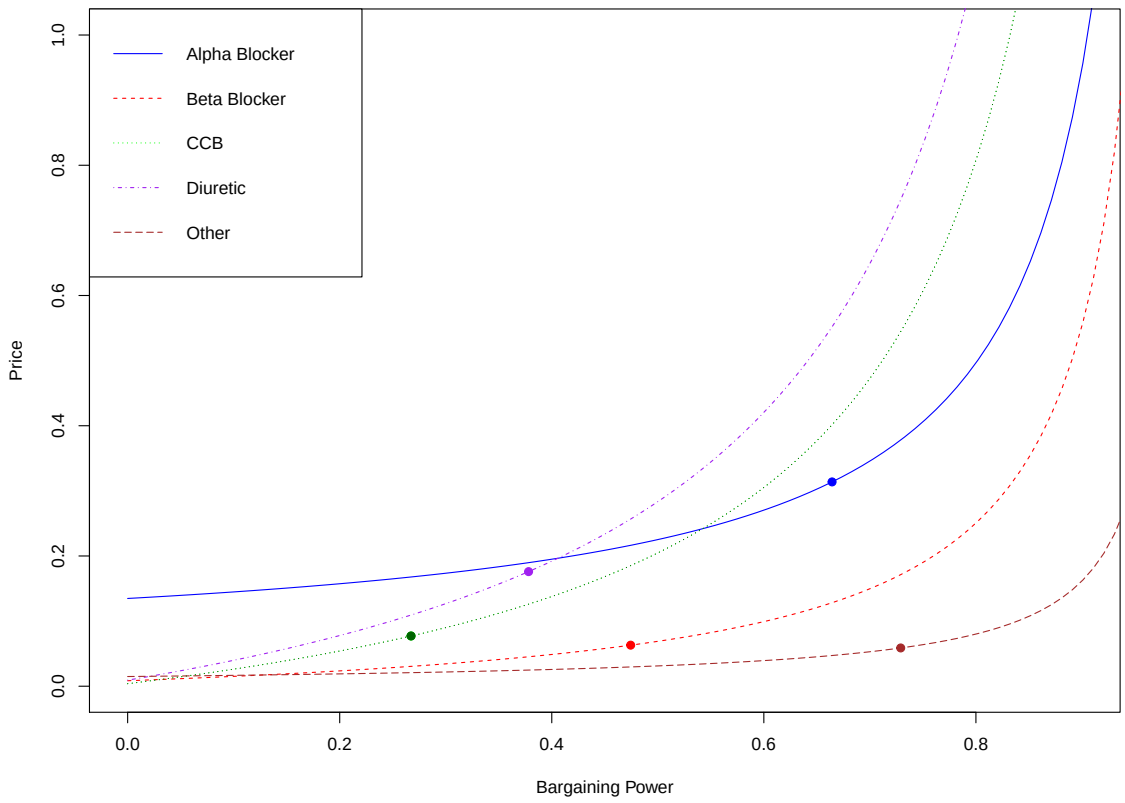

Figure 3 shows the estimated price for each level of bargaining power and each drug class. Marginal cost and own-price elasticity are held fixed at their means. Higher bargaining power indicates more seller power, while lower bargaining power indicates more bargaining power for the buyer. The points marked on each curve indicate the average bargaining power and corresponding average price for that drug class.

Appendix

Appendix A: Additional Results

This appendix provides additional results.

Table 8: Elasticities: Alpha Blockers

	Doxazosin	Pentoxifylline	Tamsulosin
Doxazosin	-0.4405 (0.2969)	0.0034 (0.0073)	0.0166 (0.1880)
Pentoxifylline		-0.5817 (0.1154)	0.0109 (0.0122)
Tamsulosin			-0.8023 (0.4594)

Standard errors in parentheses

Table 8 shows the own-price and cross-price elasticities of molecules in the alpha blocker class.

Table 9: Elasticities: Beta Blockers

	Atenolol	Bisoprolol	Carvedilol	Metoprolol	Propranolol
Atenolol	-0.0637 (0.0725)	0.0001 (0.0035)	0.0032 (0.0055)	0.0019 (0.0034)	0.0028 (0.0050)
Bisoprolol		-0.2929 (0.1301)	0.0002 (0.0041)	-0.0051 (0.0173)	0.0003 (0.0008)
Carvedilol			-0.0949 (0.1357)	0.0001 (0.0051)	0.0006 (0.0021)
Metoprolol				-0.3097 (0.1305)	0.0007 (0.0014)
Propranolol					-0.0231 (0.1119)

Standard errors in parentheses

Table 9 shows the own-price and cross-price elasticities of molecules in the beta blocker class.

Table 10: Elasticities: Calcium Channel Blockers

	Amlodipine	Diltiazem	Nifedipine	Nimodipine	Verapamil
Amlodipine	-0.0698	0.0008	0.0010	0.0009	0.0012
	(0.1566)	(0.0020)	(0.0020)	(0.0022)	(0.0026)
Diltiazem		-0.0247	0.0003	0.00003	0.00005
		(0.0499)	(0.0005)	(0.00003)	(0.00006)
Nifedipine			-0.1298	0.0002	0.0003
			(0.5857)	(0.0004)	(0.0005)
Nimodipine				-0.0603	0.0003
				(0.4438)	(0.0005)
Verapamil					-0.0222
					(0.0298)

Standard errors in parentheses

Table 10 shows the own-price and cross-price elasticities of molecules in the calcium channel blocker class.

Table 11: Elasticities: Diuretics

	Chlortalidone	Hydrochlorothiazide	Indapamide	Spironolactone
Chlortalidone	-0.1208	0.0021	0.0022	0.0022
	(0.2667)	(0.0027)	(0.0027)	(0.0038)
Hydrochlorothiazide		-0.0459	0.0021	0.0020
		(0.1744)	(0.0024)	(0.0034)
Indapamide			-0.1691	0.0019
			(0.1453)	(0.0036)
Spironolactone				-0.1120
				(0.1674)

Standard errors in parentheses

Table 11 shows the own-price and cross-price elasticities of molecules in the diuretic class.

Table 12: Elasticities: Other

	Clonidine	Hydralazine	Methyldopa
Clonidine	-0.1560	0.000001	0.000003
	(0.0696)	(0.000006)	(0.000008)
Hydralazine		-0.1991	0.000001
		(0.1082)	(0.00001)
Methyldopa			-0.1570
			(0.1188)

Standard errors in parentheses

Table 12 shows the own-price and cross-price elasticities of molecules in the other class.

Appendix B: Robustness Checks

Table 13: Price Summary Statistics Across Dosages: Atenolol

Atenolol	25mg	50mg	100mg
Average Price	0.052	0.056	0.052
Median Price	0.030	0.033	0.046
SD Price	0.123	0.120	0.024
PV_{buyer}	2.990	2.880	0.480
PV_{time}	0.171	0.252	0.152
n	216	486	176

Table 13 shows the price summary statistics across the different dosage amounts of Atenolol.

Table 14: Price Summary Statistics Across Dosages: Bisoprolol

Bisoprolol	2.5mg	5mg	10mg
Average Price	0.708	0.785	0.444
Median Price	0.560	0.300	0.323
SD Price	0.679	0.860	0.312
PV_{buyer}	1.059	0.771	0.625
PV_{time}	0.348	0.288	0.117
n	43	49	22

Table 14 shows the price summary statistics across the different dosage amounts of Bisoprolol.

Table 15: Price Summary Statistics Across Dosages: Carvedilol

Carvedilol	3.125mg	6.25mg	12.5mg	25mg
Average Price	0.181	0.216	0.189	0.247
Median Price	0.091	0.100	0.115	0.145
SD Price	0.394	0.502	0.318	.430
PV_{buyer}	2.773	2.518	2.293	2.089
PV_{time}	0.252	0.274	0.229	0.185
n	313	341	331	291

Table 15 shows the price summary statistics across the different dosage amounts of Carvedilol.

Table 16: Price Summary Statistics Across Dosages: Metoprolol

Metoprolol	25mg	50mg	100mg
Average Price	0.651	1.170	0.684
Median Price	0.600	1.150	0.336
SD Price	0.314	0.298	0.588
PV_{buyer}	0.174	0.220	0.931
PV_{time}	0.121	0.107	0.292
n	156	206	77

Table 16 shows the price summary statistics across the different dosage amounts of Metoprolol.

Table 17: Price Summary Statistics Across Dosages: Propranolol

Propranolol	10mg	40mg	80mg
Average Price	0.076	0.060	0.255
Median Price	0.060	0.020	0.180
SD Price	0.039	0.525	0.253
PV_{buyer}	0.263	6.563	0.750
PV_{time}	NA	0.125	NA
n	12	348	6

Table 17 shows the price summary statistics across the different dosage amounts of Propranolol.

Table 18: Seller Portion of Bargaining Power: Marginal Cost=80% of Minimum Price

Class	**Mean**	**Median**	**SD**	**Min**	**Max**
Total	0.453	0.397	0.317	0	1
Alpha Blockers	0.689	0.829	0.298	0.061	1
Beta Blockers	0.477	0.445	0.309	0	1
CCBs	0.273	0.197	0.227	0	1
Diuretics	0.382	0.322	0.305	0	1
Other	0.742	0.820	0.228	0.003	1

Table 18 presents bargaining power surplus summary statistics. Mean and median values closer to 0 indicate more buyer bargaining power, while values closer to 1 indicate more seller bargaining power. In this table marginal cost is set to 80% of minimum price.

Figure 4: Overall Distribution of Bargaining Power: Marginal Cost=80% of Minimum Price

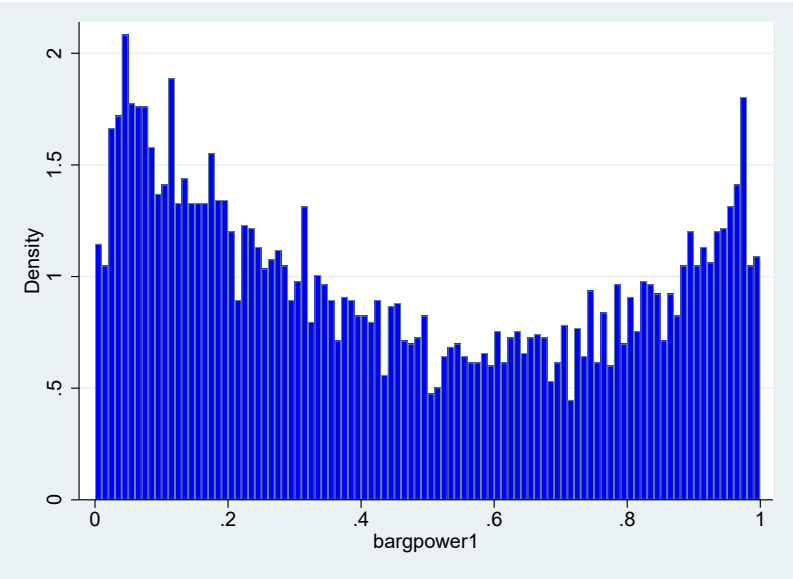

Figure 4 shows the overall distribution of bargaining power. Realizations close to 0 indicate high buyer bargaining power, and realizations close to 1 indicate high seller bargaining power. In this figure marginal cost is set to 80% of minimum price.

Figure 5: Overall Distribution of Bargaining Power by Class: Marginal Cost=80% of Minimum Price

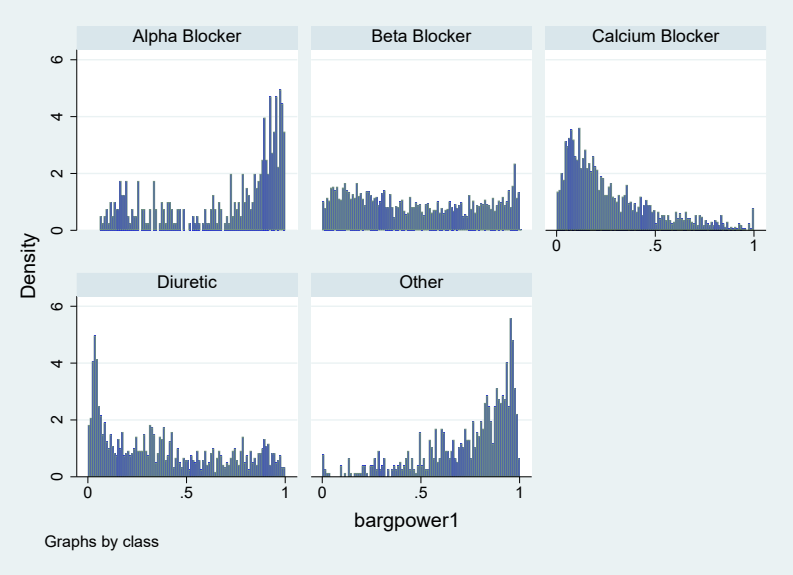

Figure 5 shows the overall distribution of bargaining power by drug class. Realizations close to 0 indicate high buyer bargaining power, and realizations close to 1 indicate high seller bargaining power. In this figure marginal cost is set to 80% of minimum price.

Table 19: Seller Portion of Bargaining Power: Marginal Cost=100% of Minimum Price

Class	**Mean**	**Median**	**SD**	**Min**	**Max**
Total	0.437	0.373	0.321	0	1
Alpha Blockers	0.602	0.749	0.358	0	1
Beta Blockers	0.471	0.441	0.310	0	1
CCBs	0.260	0.182	0.230	0	1
Diuretics	0.372	0.313	0.308	0	1
Other	0.702	0.801	0.272	0	1

Table 19 presents bargaining power surplus summary statistics. Mean and median values closer to 0 indicate more buyer bargaining power, while values closer to 1 indicate more seller bargaining power. In this table marginal cost is set to 100% of minimum price.

Figure 6: Overall Distribution of Bargaining Power by Class: Marginal Cost=100% of Minimum Price

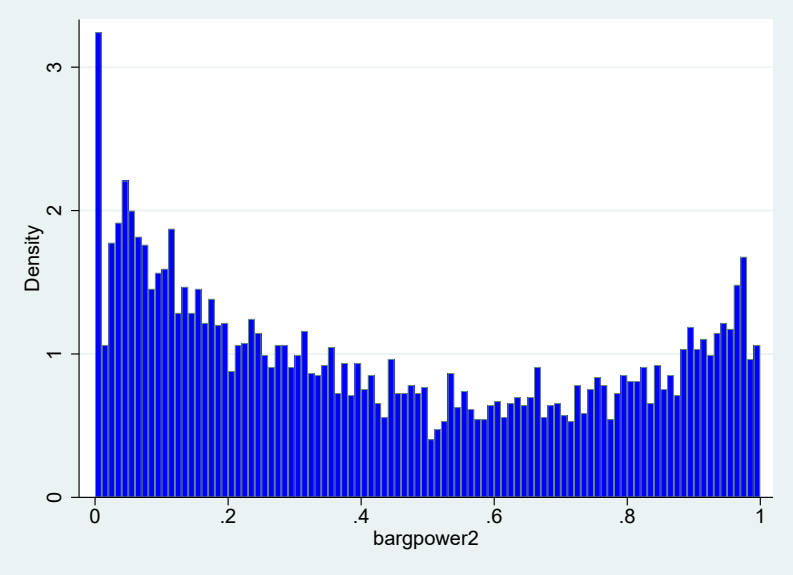

Figure 6 shows the overall distribution of bargaining power. Realizations close to 0 indicate high buyer bargaining power, and realizations close to 1 indicate high seller bargaining power. In this figure marginal cost is set to 100% of minimum price.

Figure 7: Overall Distribution of Bargaining Power: Marginal Cost=100% of Minimum Price

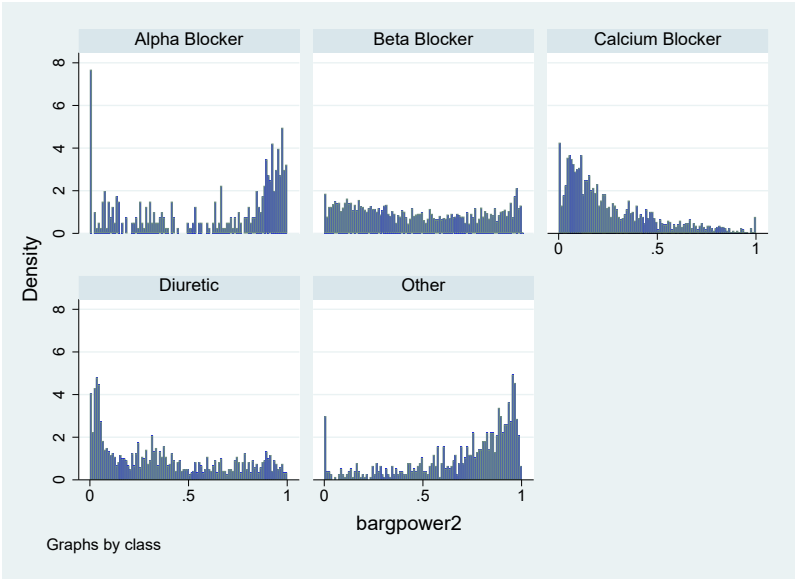

Figure 7 shows the overall distribution of bargaining power by drug class. Realizations close to 0 indicate high buyer bargaining power, and realizations close to 1 indicate high seller bargaining power. In this figure marginal cost is set to 100% of minimum price.

Table 20: Reduced form own-price elasticities

Own-price elasticity	Alpha Blockers	Beta Blockers	CCBs	Diuretics	Other
Reduced form log-log	0.278	-0.671***	-0.856***	-2.904***	-3.098***
with instruments	(0.212)	(0.049)	(0.241)	(0.342)	(0.936)

Table 20 shows the own-price elasticity for each class. This is generated by regressing the log of quantity on the log of price and the other determinants. Price is instrumented with the same instruments as in the main specification.

Appendix C: Additional Model and Methods Details

C1: Derivation of Bargaining Model's First-Order Condition

In negotiating prices, manufacturers and buyers seek to maximize the product of their respective surpluses (each weighted by their relative bargaining powers). Equation (1) captures this objective function as

$$\max_{p_{jct}} \underbrace{[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j) - d_{jct}]^{b_{jt}(c)}}_{Manufacturer\ Profits} \underbrace{[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}]^{b_{ct}(j)}}_{\text{Buyer Surplus}}, \tag{19}$$

where $\Pi_{ct}(\boldsymbol{p}_{ct}) = q_{jct}(\boldsymbol{p}_{ct})\pi_{ct}(\boldsymbol{p}_{ct})$, $d_{jct} = \Pi_{jct}(p_{jt}; C\backslash\{c\})$, and $d_{cjt} = \Pi_{cjt}(p_{jt}; J\backslash\{j\})$. In line with prior work, we assume that manufacturers are not capacity constrained, which implies that the outside option for the manufacturer from not negotiating a deal with buyer, c, for drug, j, is $d_{jct} = 0$. Now, taking the first-order condition of Equation (1) with regard to the negotiated price yields:

$$b_{jt}(c)\left[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j)\right]^{b_{jt}(c)-1}\left(\frac{\partial q_{jct}}{\partial p_{jct}}(p_{jct} - mc_j) + q_{jct}(\boldsymbol{p}_{ct})\right)\left[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}\right]^{b_{ct}(j)}$$

$$+b_{ct}(j)\left[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}\right]^{b_{ct}(j)-1}\left(\frac{\partial \Pi_{ct}(\boldsymbol{p}_{ct})}{\partial p_{jct}} - \frac{d_{cjt}}{\partial p_{jct}}\right)\left[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j)\right]^{b_{jt}(c)} = 0. \tag{20}$$

Dividing through Equation (2) by the manufacturer surplus term, $[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j) - d_{jct}]^{b_{jt}(c)}$, and the buyer surplus term, $[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}]^{b_{ct}(j)}$, we get:

$$b_{jt}(c)\left(\frac{\partial q_{jct}}{\partial p_{jct}}(p_{jct} - mc_j) + q_{jct}(\boldsymbol{p}_{ct})\right)\left[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}\right]$$

$$+b_{ct}(j)\left(\frac{\partial \Pi_{ct}(\boldsymbol{p}_{ct})}{\partial p_{jct}} - \frac{d_{cjt}}{\partial p_{jct}}\right)\left[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j)\right] = 0. \tag{21}$$

Dividing Equation (3) by $q_{jct}(\boldsymbol{p}_{ct})$ gives:

$$b_{jt}(c)\left(\frac{\partial q_{jct}}{\partial p_{jct}}\frac{(p_{jct} - mc_j)}{q_{jct}(\boldsymbol{p}_{ct})} + 1\right)\left[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}\right]$$

$$+b_{ct}(j)\left(\frac{\partial \Pi_{ct}(\boldsymbol{p}_{ct})}{\partial p_{jct}} - \frac{d_{cjt}}{\partial p_{jct}}\right)\left[(p_{jct} - mc_j)\right] = 0. \tag{22}$$

Next, dividing through by $b_{ct}(j)$ and noting that $\frac{\partial \Pi_{ct}(\boldsymbol{p}_{ct})}{\partial p_{jct}} = -q_{jct}(\boldsymbol{p}_{ct})$ and $\frac{\partial d_{cjt}}{\partial p_{jct}} = 0$, Equation (3) simplifies to:

$$q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j) = \frac{b_{jt}(c)}{b_{ct}(j)} \left(\frac{\partial q_{jct}}{\partial p_{jct}} \frac{(p_{jct} - mc_j)}{q_{jct}(\boldsymbol{p}_{ct})} + 1 \right) \left[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt} \right]. \tag{23}$$

Lastly, dividing through by $q_{jct}(\boldsymbol{p}_{ct})$ and adding mc_j to both sides we get:

$$p_{jct} = mc_j + \frac{b_{jt}(c)}{b_{ct}(j)} \left(\frac{\partial q_{jct}}{\partial p_{jct}} \frac{(p_{jct} - mc_j)}{q_{jct}(\boldsymbol{p}_{ct})} + 1 \right) \frac{[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}]}{q_{jct}(\boldsymbol{p}_{ct})}, \tag{24}$$

which is equivalent to Equation (2) (see footnote 13 in Grennan (2013) for additional details).

C2: Iterative Method Used for Counterfactual Analysis

For our counterfactual equilibrium price analysis, we use Equation (18), which is reproduced here for quick reference:

$$p_{jct} = \frac{mc_j + BP_{jct} \left[\left(1 + \frac{\partial q_{jct}}{\partial p_{jct}} \frac{p_{jct} - mc_j}{q_{jct}} \right) \left(\pi_{ct}(p) - d_{jct} \right) - mc_j \right]}{1 - BP_{jct}}.$$

Given a change in a particular bargaining determinant, we use the following iterative method to establish the new equilibrium prices:

1. Calculate a new bargaining power ratio, $\widehat{BP}_{jct}$, (using Equation (17)) based on the change from a particular bargaining determinant (e.g., Quantity, Business Relationships, Learning and Time Trend, Market Structure, or Bargaining Power Fixed Effects).

2. Given the new bargaining power ratio, $\widehat{BP}_{jct}$, we use Equation (18) to generate a new price, $\widehat{p}_{jct}$, (using the original surplus).

3. Next, we plug the generated price, $\widehat{p}_{jct}$, into the right-hand side of Equation (18) to generate a new surplus value (numerator of right-hand side Equation (18)), and generate a new predicted price, $\widehat{\widehat{p}}_{jct}$.

We repeat Step 3 until the left-hand side and right-hand sides of Equation (18) converge.