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ABSTRACT

Norton, Brandon J. Ph.D., Purdue University, August 2020. Essays on Industrial Organization and Health Economics. Major Professor: Ralph Siebert.

This dissertation consists of three essays examining the nature of pricing in the pharmaceutical industry and the behavior of physicians prescribing drugs. I use a combination of structural modeling and reduced-form econometric techniques to illuminate how factors such as bargaining, competition, and network membership can affect prices and prescribing behavior. Ultimately, these insights can be used to influence public policy goals such as reducing prescription drug costs for patients or limiting unnecessary prescribing.

In Chapter One, which is joint work with Sebastian Linde and Ralph Siebert, I focus on the determinants and effects of bargaining power on wholesale pharmaceutical drug prices. We estimate a structural bargaining model and find that large differences in bargaining power explain drug price heterogeneities across buyers, drug classes, and time periods. Our results show that transaction-specific determinants between buyers and sellers (such as transaction volume, buyer's loyalty, multiple drug purchases from the same seller, etc.) exert strong effects on buyer bargaining power and drug prices. Our counterfactuals show that group purchasing organizations achieve price reductions that vary across drug classes and that these price reductions primarily depend on buyer price sensitivity.

In the second chapter, joint with Günter Hitsch, Sebastian Linde, and Ralph Siebert, I turn to the retail prescription drug market. Here, we show that there is a significant amount of price variation for prescription drugs in the retail pharmaceutical market. Both negotiated prices (price between retail pharmacies and third-party insurers) and out of pocket prices (prices between retail pharmacies and insured pa-

tients) for a drug exhibit a high degree of price variation even when controlling for drug manufacturer, geographic location, pharmacy chain, etc. Furthermore, the nature of this price variation changes depending on if a drug is branded or generic.

In the third chapter, joint with Svetlana Beilfuss and Sebastian Linde, I examine the problem of antimicrobial resistance and how physician membership in Accountable Care Organizations (ACOs) can influence antibiotic prescribing behavior. We use a two-part structural model that accounts for selection into treatment (the ACO group), and non-treatment (control group). We then compare physician antibiotic prescribing across these groups with adjustment for volume, patient, physician, and institutional characteristics. We find that ACO affiliation reduces antibiotic prescribing by about 23% per year. Furthermore, we show that failure to account for selection into treatment results in an understating of the average treatment effect.

1. INTRODUCTION

Rising prices and lack of access to life-saving pharmaceuticals are public health problems that continue to affect patients in both the United States and globally. Complicated intellectual property protections and strange idiosyncrasies in this industry can cause prices for individual drugs to change drastically in short time periods. Over the last few years list prices, those drug prices that are paid by uninsured patients, have risen dramatically for some patented drugs like insulin. Even certain generic drugs experience massive price fluctuations. While decreasing the cost of prescription drugs seems to be a universal public policy goal, debates on how to achieve this goal have done little to actually reduce costs.

Complicating this issue further are the various agents in this industry, all with different objectives. Drug manufacturers desire strong intellectual property protection in order to maximize profits and enable the research and development of new molecules. Patients want to obtain drugs at the lowest possible cost, but also have an interest in enabling the development of future drugs. Physicians desire to give their patients the best possible care, but are insulated from the costs of that care. Third party commercial insurers want to entice patients to enroll in their plans by providing generous benefits, but face large costs of providing those benefits. Pharmacy benefit managers help insurance companies by bargaining on their behalf and can steer demand toward or away from a given drug manufacturers with the use of formularies. Retail pharmacies land somewhere in the middle of this complicated supply chain, by purchasing drugs from manufacturers and then selling them to insurance companies and patients.

In the first chapter of this dissertation I examine bargaining on the wholesale side of this market. Using a novel dataset, I am able to gain insights into the bargaining that occurs between drug manufacturers and large, wholesale buyers. This provides

a look at a side of the industry that is rarely examined due to lack of available data. I create a structural bargaining model to show that bargaining between wholesale buyers and manufacturers plays a strong role in determining the actual prices faced, rather than just market characteristics such as costs and demand. I then show what particular characteristics of buyers and sellers are the most important in determining the negotiated price. I use these characteristics to create a counterfactual experiment where I examine what would happen in the case of a coalition of buyers acting together versus a single buyer negotiating alone. Insights from this paper can be used to predict how changes in bargaining abilities might ultimately influence the prices faced by large, wholesale buyers.

In the second chapter I turn to the retail market. Here, I again examine bargaining between buyers and sellers, but this time on the retail side. Large pharmacy chains, such as CVS, Wal-mart, etc. sell prescribed drugs to patients. In this case, we consider patients that are covered by third-party health insurance plans. The pharmacy, then, received payments not only from the patient in the form of copays and deductibles, but also from the insurer in the form of a contractually negotiated reimbursement. We examine what factors influence this reimbursement rate received by retail pharmacies, as well as the out of pocket costs faced by the insured patient.

In the third and final chapter I switch my focus to physician prescribing behavior. In this chapter I examine the problem of antimicrobial resistance. Bacterial infections are becoming increasingly resistant to existing antibacterial drugs and few, or no, new antibiotics are being created. One channel to combat this problem is reducing unnecessary antibiotic prescriptions. I examine how network effects, in this case membership in an Accountable Care Organization, can influence a physician's decision to prescribe antibiotics. We show that membership in such an organization can decrease antibiotic prescribing significantly. Moreover, we show that failure to take unobserved characteristics into account can vastly understate the magnitude of this effect.

These chapters highlight some potential channels that could help mitigate the problems of high drug costs and antimicrobial resistance. Lack of data has hampered research effort in this industry. By using three different datasets, I am able provide some insight into how bargaining and network affiliation can effect drug prices and physician prescribing behavior. Using these, and similar, data sources, future research should be able to provide even more solutions to these complex and important problems.

2. THE EFFECT OF BARGAINING POWER DETERMINANTS ON PHARMACEUTICAL PRICES

In many markets different buyers pay different prices for the same good rather than paying a uniform market price. Price variations are, in fact, observed in a variety of markets, such as health care markets (Cooper et al. (2019)), wholesale, and retail markets (DellaVigna and Gentzkow (2019); Goldberg and Verboven (2001); Hitsch et al. (2019)). In most markets, 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

[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.

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, 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.

[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).

[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.

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 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

[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.

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 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, 63% 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, 42% 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.

In the last section, we conduct a counterfactual experiment to examine the effectiveness of city level group purchasing as compared to hospitals independently purchasing their antihypertensive drugs. As such, we are able to explore the price gains that stem from cities acting as Group Purchasing Organizations (GPOs) on behalf of their city hospitals. GPOs are agents that negotiate on behalf of multiple buyers collectively. They are used in many industries and attempt to leverage bargaining skills and a larger buyer size to achieve price reductions for their member buyers. We explain the specific structure of GPOs in our setting in the relevant section. We find that GPOs are successful in improving buyer bargaining power and reducing prices in all of our drug classes, and further that the magnitude of observed price gains depend on transaction volumes and drug class price sensitivity. Given these features, we find that the effectiveness of a GPO varies considerably across different drug classes.

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.

2.1 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 2.1).

Table 2.1.
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 2.1 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.

It should be noted that antihypertensive drugs are commonly considered and prescribed as substitutes rather than complements.[7] Antihypertensive drugs generally

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

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 antihypertensive 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

[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.

manufacturers are typically domestic firms that sell multiple drugs. We complement the transaction data with demographic data taken from the Brazilian census.

The 1993 Public Procurement Act sets the rules municipal governments must abide by when purchasing pharmaceuticals. Brazilian public purchasers must engage in various types of procurement auctions to purchase commodities such as pharmaceuticals. These auctions may be either electronic or physical, and cities must allow open bidding. Auctions may also use different mechanisms such as first-price sealed bid, English, or two stage auctions (Arvate et al. (2013)). Furthermore, per the 2002 Federal Act No 10.520, generic (standardized) drugs auctions may be followed by bargaining in order to ensure more advantageous pricing. That is, following the establishment of a winning bidder, negotiations concerning the final price may occur between the winner and the local municipality. In cases where these price negotiations with the winning bidder fall through, the other bidders are called to negotiate.[10] Since we have many separate municipalities, and each municipality may use different auction mechanisms, we use a Nash bargaining model that generalizes the various procurement auctions that might be used across municipalities, and most importantly fully captures the negotiation phase of these procurements. Additionally, some experimental work has shown that with many sellers there is little difference between first-price auctions and multilateral negotiations (Thomas and Wilson (2002)).

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.[11]

[10]For additional detail, see https://practiceguides.chambers.com/practice-guides/public-procurement-government-contracts-2020/brazil (accessed 02/24/20) or Jenny and Katsoulacos (2016)

[11]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.

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 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.[12] 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, as well as price variation, for a DDD across different amounts of the active ingredient for all of the drugs in the beta blocker class. The DDD for each drug is a similar price regardless of the amount of the active ingredient. Additionally, price variation is similar regardless of the amount of the active ingredient. The similar prices and price variation ensures we are not artificially creating price variation by aggregating across dosage amounts.[13]

Table 2.1, columns 1 through 5, shows summary statistics on prices across drugs. Throughout the paper, prices are expressed in Brazilian Reals.[14] 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

[12]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.
[13]See Table 2.14 through Table 2.18 in Appendix B.
[14]Currently, a U.S. Dollar is worth about 4 Brazilian Reals.

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 2.1 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[15]. Therefore, price variations are unlikely explained by different amounts of the active ingredients. 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 high 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

[15]See Table 2.14 through Table 2.18 in Appendix B.

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.

2.2 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.[16] 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 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}.

[16] 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).

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.[17] 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.

2.2.1 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:

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

$$\max_{p_{jct}} \left[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_{jt}) - d_{jct}\right]^{b_{jt}(c)} \left[q_{jct}(\boldsymbol{p}_{ct})\pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}\right]^{b_{ct}(j)}. \tag{2.1}$$

The first term in Equation (2.1)—$[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j) - d_{jct}]$—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_{jt} is the marginal cost of drug j. 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 (2.1)—$[q_{jct}(\boldsymbol{p}_{ct})\pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}]$—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.[18]

Taking first-order conditions of Equation (2.1) with respect to the drug price and solving for the bargained price, we get:

$$p_{jct} = mc_{jt} + \frac{b_{jt}(c)}{b_{ct}(j) + b_{jt}(c)} \left[\left(1 + \frac{\partial q_{jct}}{\partial p_{jct}} \frac{p_{jct} - mc_{jt}}{q_{jct}}\right)\left(\pi_{ct} - d_{cjt}\right) + p_{jct} - mc_{jt}\right]. \tag{2.2}$$

Equation (2.2) implies that in order for price to be above marginal cost, it must be the case that $\left(1 + \frac{\partial q_{jt}}{\partial p_{jt}} \frac{p_{jt} - mc_{jt}}{q_{jt}}\right) > 0$, or put differently that $\left(\frac{\partial q_{jt}}{\partial p_{jt}} \frac{p_{jt} - mc_{jt}}{q_{jt}}\right) \in [-1, 0]$ and that $\pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}(\boldsymbol{p}_{jt}; J_{ct}\backslash\{j\}) > 0$ (see Grennan, 2013).[19]

[18] 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, $d_{jct} = 0$.

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

Rearranging Equation (2.2), the relative bargaining power between the seller and buyer of drug j and city c at time period t is given by:

$$\frac{b_{jt}(c)}{b_{ct}(j)+b_{jt}(c)} = \frac{p_{jct}-mc_{jt}}{\left(1+\frac{\partial q_{jct}}{\partial p_{jct}}\frac{p_{jct}-mc_{jt}}{q_{jct}}\right)\left(\pi_{ct}-d_{cjt}\right)+p_{jct}-mc_{jt}}. \tag{2.3}$$

Equation (2.3) 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 (2.3) approaches 0, the buyer gains on bargaining power. Alternatively, a value closer to 1 indicates increased bargaining power of the seller.

The relative bargaining power of buyers and sellers can be retrieved based on observables (p_{jct} and q_{jct}), the mc_{jt}, 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), 0.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 10-12%, which translates into a drug-specific marginal cost that is at most 90% 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.[20] Additionally, marginal cost is allowed to vary over time. 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 cost's relation to the lowest transaction price. In one check we set marginal cost to 85% of the lowest transaction price and in another we set marginal cost to 95% of the lowest transaction price. The results show less than a 2% difference in the overall bargaining power distribution.[21]

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):

$$\begin{aligned} E(\pi_{ct}(p_{jct})) &= \frac{1}{\alpha_i} E\left[\underset{j\in J_{ct}}{max}\left(d_{cjt}+\epsilon_{ijct}\right)\right] \\ &= \frac{1}{\alpha_i}\ln\left(\sum_{j\in J_{ct}}\exp(d_{jct})\right)+K, \end{aligned} \tag{2.4}$$

where α_i is the disutility of price, which will be estimated in the demand equation, and K is a constant. Note, that Equation (**??**) 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

[20] We distinguish between five regions in Brazil: North, Northeast, Center-West, Southeast, and South.

[21] See Table 2.19 and Table 2.20 as well as Figure 2.5 through Figure 2.5 in Appendix B.

Equation (**??**)), 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)).

2.2.2 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 (2.4)) 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.[22] The indirect utility is specified as follows:

$$u_{ijct} = \alpha_i p_{jct} + X_j\beta + \xi_{jct} + \epsilon_{ijct}. \tag{2.5}$$

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,

[22]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).

and β is a parameter of interest. We also allow 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.

Estimation of Demand Parameters

The heterogeneous parameter, α_i, from Equation (2.5) 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:

$$\alpha_i = \alpha + \Sigma\nu_i, \quad \nu_i \sim N(0, I), \tag{2.6}$$

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:

$$\delta_{jct} = \alpha p_{jct} + X_j\beta + \xi_{jct}. \tag{2.7}$$

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:

$$u_{ijct} = \delta_{jct} + \mu_{ijct} + \epsilon_{ijct} \tag{2.8}$$

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:

$$A_{jct} = \big\{(\nu_i, \epsilon_{ijct}) | U_{ijct} \geq U_{ikct}\big\}. \tag{2.9}$$

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

$$s_{jct} = \int_{A_{jct}} dF(\nu, \epsilon) = \int_{A_{jct}} dF_\nu(\nu) dF_\epsilon(\epsilon). \tag{2.10}$$

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:

$$s_{ijct} = \int_{A_{jct}} \frac{exp(\delta_{jct} + \mu_{ijct})}{\sum_{j=0}^{J} exp(\delta_{jct} + \mu_{ijct})} dF_\nu(\nu). \tag{2.11}$$

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:

$$\hat{s}_{jct} = \int_{A_{jct}} s_{ijct} dF_\nu(\nu) = \frac{1}{N}\sum_{i=1}^{N} s_{icjt} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{exp(\delta_{jct}+\mu_{ijct})}{\sum_{l=0}^{J} exp(\delta_{lct}+\mu_{ilct})}\right). \quad (2.12)$$

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).[23]

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:

$$\eta_{jjct} = \frac{\partial s_{jct}}{\partial p_{jct}}\frac{p_{jct}}{s_{jct}} = \frac{-p_{jct}}{s_{jct}}\int_{A_{jct}} \alpha_i s_{ijct}(1-s_{ijct}) dF_\nu(\nu). \quad (2.13)$$

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 (2.3) to back out the bargaining power.

2.3 Results

2.3.1 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}.

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

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 2.2 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.[24] Half-life measures how quickly a drug begins to become 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

[24]We also controlled for different tablet sizes which do not have a significant effect. This result confirms that tablets of specific sizes do not have a significant effect on demand and no significant power to explain the price variations.

Table 2.2.
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 2.2 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.

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 2.2 also reports the own-price elasticities across drug classes.[25] Own-price elasticity estimates vary across drug classes and take on values from -1 to 0 (see Table 2.2). 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

[25]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.

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 and Lettau (2004) finds the elasticity of insurance coverage is -0.6. Finally, small 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 2.21 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 (**??**). The surplus calculation is then used to evaluate the difference $(\pi_{ct} - d_{jct})$, as shown in Equation (2.3), which then enables us to calculate the relative bargaining power ratio as shown on the left-hand side of Equation (2.3). 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.

2.3.2 Heterogeneity of Bargaining Ability

Table 2.3 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 2.3), 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 37.1% of the bargaining surplus, on average. The buyer received the remainder, 62.9%, of the bargaining surplus across all drugs. The distribution of bargaining outcomes 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 2.3.2 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 somewhat bimodal.

Turning to the bargaining power ratios across drug classes, Table 2.3 shows that sellers achieve higher bargaining power for alpha blockers and other drug classes, about 58% and 62%, respectively. In contrast, buyers achieve higher bargaining power in the beta blocker, calcium channel blocker and diuretic classes, where they get about 59%, 80% and 71% 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

Table 2.3.
Seller Portion of Bargaining Power

Class	Mean	Median	SD	Min	Max
Total	0.371	0.261	0.331	0	1
Alpha Blockers	0.583	0.645	0.341	0.023	1
Beta Blockers	0.407	0.329	0.328	0	1
CCBs	0.200	0.106	0.229	0	1
Diuretics	0.289	0.126	0.316	0	1
Other	0.624	0.727	0.304	0.001	0.999

Table 2.3 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.

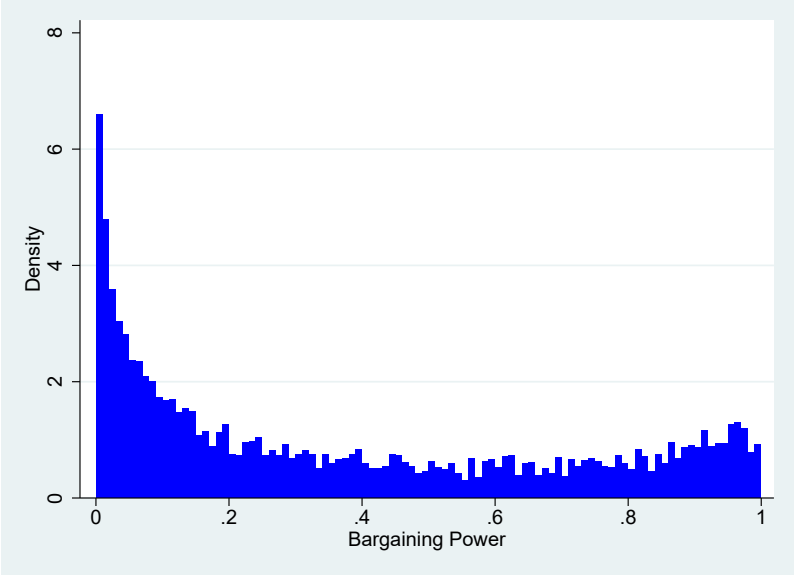

Figure 2.1. Overall Distribution of Bargaining Power

Figure 2.3.2 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.

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 2.3.2 illustrates large heterogeneities in bargaining power realizations across drug classes. The figures on the alpha blockers and other drug classes show a mass toward the upper end of the bargaining power distribution. The calcium channel blocker and diuretic classes are characterized by lower bargaining power realizations with large masses toward the buyer end of the distribution. The beta blocker class has a more uniform distribution of bargaining outcomes. 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.

Figure 2.2. Bargaining Power Distribution Across Drug Classes

Figure 2.3.2 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.

2.3.3 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 (2.3), that is, $((1+\frac{\partial q_{jct}}{\partial p_{jct}}\frac{p_{jct}-mc_{jt}}{q_{jct}})(\pi_{ct}-d_{jct})+p_{jct}-mc_{jt})$. 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 (2.3) we get:

$$p_{jct}-mc_{jt}=BP_{jct}AV_{jct}. \tag{2.14}$$

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

$$ln(p_{jct}-mc_{jt})=ln\left(BP_{jct}\right)+ln(AV_{jct}). \tag{2.15}$$

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.[26]

$$Price\ Variation\ due\ to\ bargaining=\frac{V\left(ln\left(BP_{jct}\right)\right)}{V\left(ln\left(BP_{jct}\right)\right)+V(ln(AV_{jct}))}. \tag{2.16}$$

Table 2.4 reports the price variation due to bargaining power. This variation ranges from about 23% to 50% across the different drug classes and 42.4% overall. This

[26]See Grennan (2014), Section 5.1

means that differences in bargaining ability are able to explain 42.4% of the overall price variation (the rest is explained by other demand and supply factors).

Figure 2.3.3 illustrates the different outcomes of bargaining strength across drug classes. The figure illustrates that changes in bargaining power have very different effects on prices.[27]

While an improvement in bargaining power can have strong price-reducing effects in the beta blocker, calcium channel blocker, and diuretic classes, it has a smaller effect 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.

[27]Figure 2.3.3 will be explained in more detail in a later section of the paper.

Table 2.4.
Price Variation from Bargaining Power

Class	**Price Variation from Bargaining (%)**	**Variation of Bargaining**	**Variation of Added Value Terms**
Alpha Blocker	22.7	0.937	3.197
Beta Blocker	38.0	2.269	3.702
CCBs	42.0	2.378	3.281
Diuretic	49.7	3.118	3.160
Other	27.6	0.946	2.481
Total	42.4	2.552	3.473

Table 2.4 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).

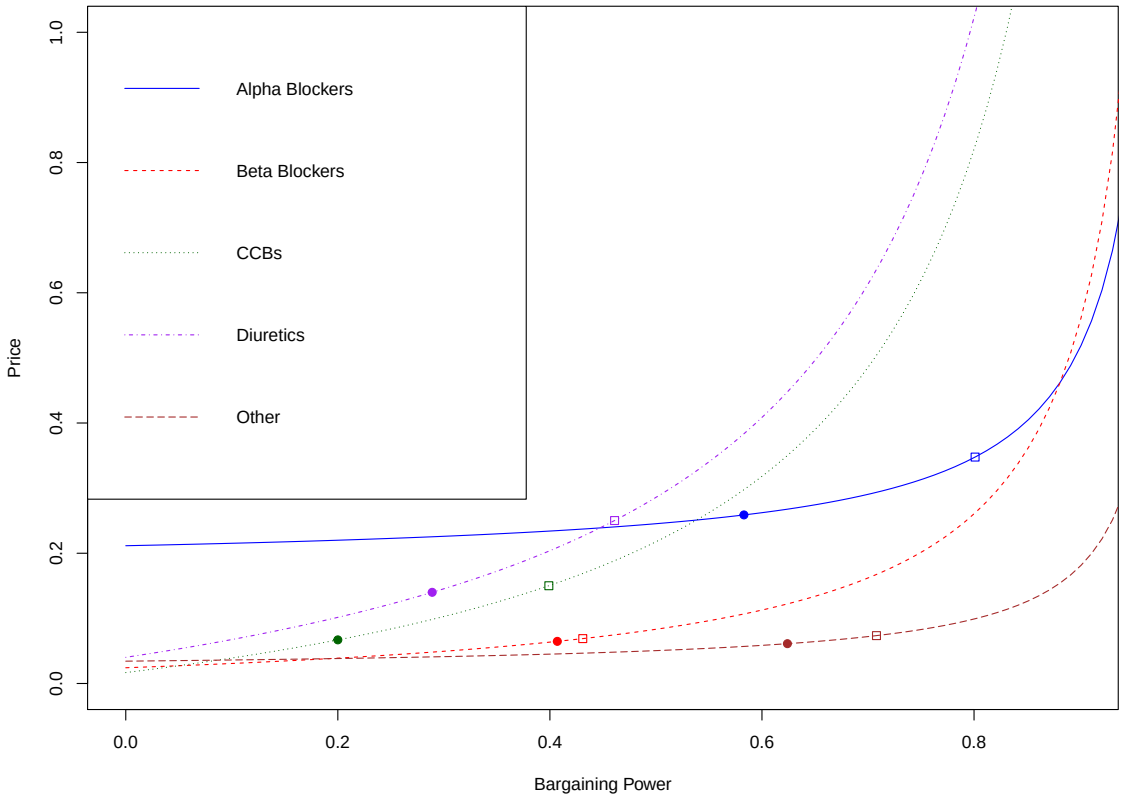

Figure 2.3. Price vs Bargaining Power for each Drug Class

Figure 2.3.3 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 solid circles marked on each curve indicate the average bargaining power and corresponding average price for that drug class.The hollow squares indicate the average bargaining power and corresponding average price if hospitals were to negotiate separately.

2.3.4 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:

$$
\begin{aligned}
ln(BP_{jct}) = & \underbrace{\beta_1 ln(q_{jct})}_{\text{Quantity}} \\
& \underbrace{+\beta_2 Loyalty_{cjt} + \beta_3 Multiple\ Drug\ Purchases_c + \beta_4 Renegotiation_{jct}}_{\text{Business Relationships}} \\
& \underbrace{+\beta_5 Cumulative\ Transactions_{ct} + \beta_6 Period_t}_{\text{Learning and Time Trend}} \\
& \underbrace{+\beta_7 Population_c + \beta_8 Number\ of\ Hospitals_c + \beta_9 Number\ of\ Sellers_c}_{\text{Market Structure}} \\
& \underbrace{+\beta_{10} Average\ ln(BP)_{-class,c} + \beta_{11} Average\ ln(BP)_{-drug,c}}_{\text{Bargaining Power Fixed Effect}} + \epsilon_{jct}.
\end{aligned}
\tag{2.17}
$$

The dependent variable, *BP*, is the bargaining power ratio, as previously defined. Table 2.5 shows summary statistics for the independent variables in Equation (2.17).

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 (2.17) 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

Table 2.5.
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 2.5 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.

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.[28] 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.[29]

The next relationship variable, *Multiple Drug Purchases*, measures the total number of *different* drugs that a buyer has purchased from the same 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.

[28]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.

[29]Note that *Loyalty* only describes the observed percentage of transactions a buyer makes with the same seller. We do not take a stand on whether this measures actual loyalty the buyer feels toward the seller or if it instead captures buyer inertia or switching costs.

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 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.[30] 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.

[30]Table 2.5 reports that an average buyer has completed 36 transactions throughout the time period.

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 (2.17) are shown in Table 2.6. Due to the construction of the bargaining power variable (see Equation (2.3)), a negative regression coefficient on an explanatory 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 (and 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 two of the drug classes (and overall). This result provides evidence that a larger drug variety purchased from the same seller is associated with higher buyer bargaining power.

Table 2.6.
Determinants of Bargaining Power

Variable	**Alpha Blockers**	**Beta Blockers**	**CCBs**	**Diuretics**	**Other**	**Total**
ln(q)	-0.071***	-0.143***	-0.264***	-0.296***	-0.106***	-0.202***
	(0.024)	(0.012)	(0.018)	(0.025)	(0.019)	(0.008)
Loyalty	-0.828***	-0.602***	-0.463***	-0.800***	0.130	-0.102*
	(0.193)	(0.010)	(0.137)	(0.180)	(0.124)	(0.059)
Multiple Drug Purchases	-0.005	-0.024***	-0.004	-0.055***	-0.014	-0.018***
	(0.019)	(0.009)	(0.014)	(0.016)	(0.010)	(0.006)
Renegotiation	0.004	0.082***	0.013	0.237***	-0.178***	0.105***
	(0.058)	(0.011)	(0.031)	(0.043)	(0.055)	(0.010)
Cumulative Transactions	-0.002	0.006**	0.003	-0.013***	0.012***	0.000
	(0.005)	(0.002)	(0.003)	(0.004)	(0.004)	(0.001)
Period	0.012	-0.013***	-0.008	0.019**	-0.024***	-0.002
	(0.010)	(0.005)	(0.007)	(0.008)	(0.007)	(0.003)
Population	-0.027	0.455	-6.084***	0.380	-0.359	0.016
	(1.214)	(0.795)	(1.723)	(3.115)	(0.595)	(0.469)
Number of Hospitals	0.010	-0.005	0.025***	0.015	0.004	0.004*
	(0.007)	(0.004)	(0.006)	(0.010)	(0.004)	(0.002)
Number of Sellers	-0.020	-0.044***	-0.060***	0.008	-0.038***	-0.012***
	(0.016)	(0.007)	(0.011)	(0.012)	(0.011)	(0.005)
Average BP, other classes	0.412	0.884***	1.074***	2.189***	0.624*	
	(0.433)	(0.196)	(0.316)	(0.362)	(0.356)	
Average BP, other drugs	1.040***	0.616***	1.276***	-0.869***	0.981***	
	(0.180)	(0.147)	(0.306)	(0.221)	(0.238)	
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 2.6 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).

The regression results for the *Renegotiations* variable turns out to be significant and positive in two of the drug classes (and overall). 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 also not consistently significant nor associated with buyer or seller bargaining power. This result shows that time-varying changes are not strongly associated with improvements in either buyer or seller bargaining power. Our study suggests learning does not consistently improve buyer or seller bargaining power, while business relationships have 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 not statistically significant in four of the five drug classes, but it is statistically significant and associated with buyer power in one drug class, CCBs. A larger *Number of Hospitals* in a city reduces buyer bargaining power in one drug class (also CCBs) and has a small but statistically significant effect overall. 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 (and overall). 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.

2.3.5 The Effect of Bargaining Power Determinants on Price

While our estimation results, as shown in Table 2.6, 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 a change in the bargaining determinants, business relationship, learning and time trends, and market structure characteristics, see Table 2.6) translate into price changes.

We can evaluate the price effect with respect to changes in bargaining power based on Equation (2.2):

$$p_{jct} = \frac{mc_{jt} + BP_{jct}\left[\left(1 + \frac{\partial q_{jct}}{\partial p_{jct}}\frac{p_{jct}-mc_{jt}}{q_{jct}}\right)\left(\pi_{ct}(p) - d_{jct}\right) - mc_{jt}\right]}{1 - BP_{jct}} \tag{2.18}$$

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 2.3.3. 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 2.6. Using Equation (2.18) and the regression results, we evaluate the effect of a 10% increase in a bargaining determinant on price.[31] Table 2.7 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.

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

Table 2.7.
Change in Price Resulting from a Change in a Determinant

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

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.

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 2.3.3. 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.

2.4 Group Purchasing Organization Counterfactual

Most hospitals in the United States utilize Group Purchasing Organizations (GPOs) for at least some of their spending on pharmaceuticals (Burns and Lee (2008)). GPOs argue that they are able to reduce their members' costs by both increasing quantity purchased and "employing market intelligence and product expertise that no single member could afford" (Hu et al. (2012)). Previous work has found that the benefits of GPO membership can depend on factors such as number of members, size of members, and profit-sharing (Hu et al. (2012)). We examine this issue in our setting by constructing a counterfactual in which the hospitals in each city purchase antihypertensive drugs independently from the city. Thus, the city acts as a GPO for its member hospitals.

In Section 3.1 we discuss price limits at the extremes of the bargaining power ratio.[32] When a buyer holds all of the available bargaining surplus, the market structure is competitive and price is equal to marginal cost. As marginal cost is determined solely by the supplier, changing the number of buyers will not affect marginal cost. Thus, the price floor (where $p = mc$) is unchanged by the counterfactual.

As the bargaining power ratio approaches 1, market structure approaches Bertrand-Nash price setting. Here, sellers set prices to maximize profits while accounting for competitors' best response functions. Examining Equation (2.18) shows that in the counterfactual, when the number of buyers increase, the price ceiling also increases

[32]See Equation (2.2) and footnote 19.

relative to the price ceiling in reality, where cities act as GPOs. This price ceiling increase is driven by two terms in Equation (2.18). First, quantity decreases in the counterfactual. Since there is more than one hospital in a city, the total amount of a drug purchased in that city will now be divided among the hospital buyers. Thus, each individual hospital purchases less quantity than the city overall. Since quantity decreases, the $\frac{p_{jct}-mc_{jt}}{q_{jct}}$ term will increase. Since this term is in the numerator of Equation (2.18), price will increase. The second factor that could drive an increase in the price ceiling for hospital buyers is the $\pi_{ct}(p) - d_{jct}$ term. Since there are now more overall buyers, there is more potential for certain buyers to have a high consumer surplus when purchasing a certain drug ($\pi_{ct}(p)$). Additionally, for the same reason, there is more potential for buyers to have a high disagreement payoff (d_{jct}). These factors together result in the potential price ceiling being higher for hospital buyers than for city buyers.

Since the price floor in both situations is the same, and the price ceiling is higher for hospital buyers, the price range faced by GPOs are a subset of the price range faced by individual buyers. Due to this market structure effect, the theory predicts that, on average, prices should be lower for GPOs than for individual buyers. In order to test this theory, and to predict precisely how much lower the prices faced by GPOs are, we use our structural model and our reduced-form regression coefficient estimates to recalculate both bargaining power and prices for hospital buyers.

To calculate the counterfactual we first adapt the bargaining determinants to the hospital level as follows. We divide the quantity purchased by the city among the hospitals in that city. Since we have no data on the size of hospitals, we divide the quantity uniformly among the hospitals. *Loyalty* and *Multiple Drug Purchases* remain the same as the city. Since *Loyalty* is measured as a percentage and there is no reason to assume an individual hospital is more or less likely to switch sellers it remains

the same as the city. *Multiple Drug Purchases*, which is measured as the total number of products a buyer purchases from the same seller, might in general be lower for individual hospitals since they will make fewer overall transactions. However, since there is no systemic way to know how much lower, we leave it the same as the city. This will make our GPO results conservative as the hospital buyer in the counterfactual is more like the city buyer than they would be in reality. *Renegotiation* is recalculated at the hospital level since individual hospitals should have a better understanding of their future demand than the city. *Population* is divided among hospitals in the same way as quantity, *Number of Hospitals* is set to 1, and *Number of Sellers* is unchanged since individual hospitals would have the same set of manufacturers to choose from as the city buyer. Since we have no information on the idiosyncratic bargaining ability of individual hospitals, we choose to leave *Average* $ln(BP)_{-class}$ and *Average* $ln(BP)_{-drug}$ for each hospital the same as their city counterpart. This assumption means that each individual hospital is as good a bargainer as the city overall. While this is likely not realistic, it, as before, makes our counterfactual results conservative. If the GPO (the city in our setting) was a better bargainer than its individual members, that channel would make the differences in bargaining power greater than what we report.

After adjusting these variables, we calculate a new $\hat{BP}_{jht}$ using Equation (2.17) where the subscript h now refers to a hospital, rather than city, buyer. We can now use Equation (2.18) to calculate $\hat{p}_{jht}$ by substituting in $\hat{BP}_{jht}$ for BP_{jct}.[33] Table (2.8) shows the results of the counterfactual.

The first three columns show what would happen to bargaining power if hospitals were forced to negotiate on their own. Bargaining power shifts toward the seller for each drug class, though the magnitude of the shift is very different across drug classes.

[33]See Appendix C2 for details.

Table 2.8.
Hospital Buyers Counterfactual

Drug Class	**Mean BP (city buyers)**	**Mean BP (hospital buyers)**	**Percentage Change (BP)**	**Mean Price (city buyers)**	**Mean Price (hospital buyers)**	**Percentage Change (Price)**
Alpha Blockers	0.583	0.801	37	0.259	0.348	34
Beta Blockers	0.407	0.431	6	0.065	0.069	6
CCBs	0.200	0.399	100	0.070	0.150	124
Diuretics	0.289	0.461	60	0.140	0.250	79
Other	0.624	0.708	13	0.061	0.074	20

Table 2.8 presents the average change in bargaining power and price that would occur in each drug class if hospitals within a city bargained separately.

Columns 4 through 6 shows the effect on prices. If hospitals negotiated separately they would face higher prices in all drug classes, but prices would be only marginally higher (6%) for Beta Blockers. Calcium Channel Blockers, on the other hand, would be 124% more expensive. The other three drug classes fall somewhere in between. This result is shown graphically in Figure (2.3.3). The solid dot shows the mean bargaining power and corresponding price for each drug class with city buyers, while the hollow square shows the counterfactual hospital buyers. It is easy to see how the heterogeneous effects of the counterfactual are driven by the difference in slopes of the price function for each drug class. Within the relevant range of the counterfactual, Alpha Blockers, Beta Blockers, and Other all have relatively flat slopes while CCBs and Diuretics have relatively steep slopes. These different slopes are driven primarily by the $\Big(\pi_{ct}(p) - d_{jct}\Big)$ term from Equation (2.18), which is the difference in buyer's surplus when they purchase drug j versus not purchasing drug j. This term, in turn, is driven by disutility of price, α_i (see Equation (**??**)). Looking back at the first two rows of Table (2.3) we see that both the mean and SD of α_i is lower for CCBs and Diuretics than the other drug classes. Hence, it is this lower sensitivity to price that drives large changes in price from changes in bargaining power.

The main takeaway from our counterfactual is that the benefits of GPO membership are highly dependent on the specific product and it is the buyer's sensitivity to price that drives the differences in the benefit. Thus, even for products as closely related as antihypertensive drugs, there can be very disparate effects on price, and hence also on benefits, from GPO membership.

2.5 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 out-

comes, 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 2.3.3. 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 construct a counterfactual experiment in which hospitals are forced to negotiate individually instead of collectively via their city governments. This mimics the negotiating structure seen in the US and other countries by casting city governments in the role of Group Purchasing Organizations (GPOs). We find that for all of our drug classes, GPO membership increases bargaining power for the buyer and reduces prices. More importantly, we find that buyer's price sensitivity drives the variation of the magnitudes of these price reductions across drug classes even though antihypertensive drugs are similar products. Ultimately, we show that the benefits of GPO membership greatly depend on the specific product being negotiated.

Appendix A: Additional Results

This appendix provides additional results.

Table 2.9.
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 2.9 shows the own-price and cross-price elasticities of molecules in the alpha blocker class.

Table 2.10.
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 2.10 shows the own-price and cross-price elasticities of molecules in the beta blocker class.

Table 2.11.
Elasticities: Calcium Channel Blockers

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

Standard errors in parentheses

Table 2.11 shows the own-price and cross-price elasticities of molecules in the calcium channel blocker class.

Table 2.12.
Elasticities: Diuretics

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

Standard errors in parentheses

Table 2.12 shows the own-price and cross-price elasticities of molecules in the diuretic class.

Table 2.13.
Elasticities: Other

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

Standard errors in parentheses

Table 2.13 shows the own-price and cross-price elasticities of molecules in the other class.

Appendix B: Robustness Checks

Table 2.14.
Price Summary Statistics for One DDD 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 2.14 shows the price summary statistics for one defined daily dose across the different dosage amounts of Atenolol.

Table 2.15.
Price Summary Statistics for One DDD 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 2.15 shows the price summary statistics for one defined daily dose across the different dosage amounts of Bisoprolol.

Table 2.16.
Price Summary Statistics for One DDD 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	0.430
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 2.16 shows the price summary statistics for one defined daily dose across the different dosage amounts of Carvedilol.

Table 2.17.
Price Summary Statistics for One DDD 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 2.17 shows the price summary statistics for one defined daily dose across the different dosage amounts of Metoprolol.

Table 2.18.
Price Summary Statistics for One DDD 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 2.18 shows the price summary statistics for one defined daily dose across the different dosage amounts of Propranolol.

Table 2.19.
Seller Portion of Bargaining Power: Marginal Cost=85% of Minimum Price

Class	**Mean**	**Median**	**SD**	**Min**	**Max**
Total	0.383	0.279	0.330	0	1
Alpha Blockers	0.616	0.709	0.328	0.036	1
Beta Blockers	0.415	0.352	0.325	0	1
CCBs	0.209	0.117	0.228	0	1
Diuretics	0.300	0.145	0.314	0	1
Other	0.649	0.745	0.288	0.002	0.999

Table 2.19 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 85% of minimum price.

Table 2.20.
Seller Portion of Bargaining Power: Marginal Cost=95% of Minimum Price

Class	**Mean**	**Median**	**SD**	**Min**	**Max**
Total	0.356	0.236	0.334	0	1
Alpha Blockers	0.533	0.578	0.357	0.011	1
Beta Blockers	0.397	0.307	0.331	0	1
CCBs	0.190	0.090	0.231	0	1
Diuretics	0.275	0.107	0.319	0	1
Other	0.587	0.713	0.328	0.001	0.999

Table 2.20 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 95% of minimum price.

Table 2.21.
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 2.21 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.

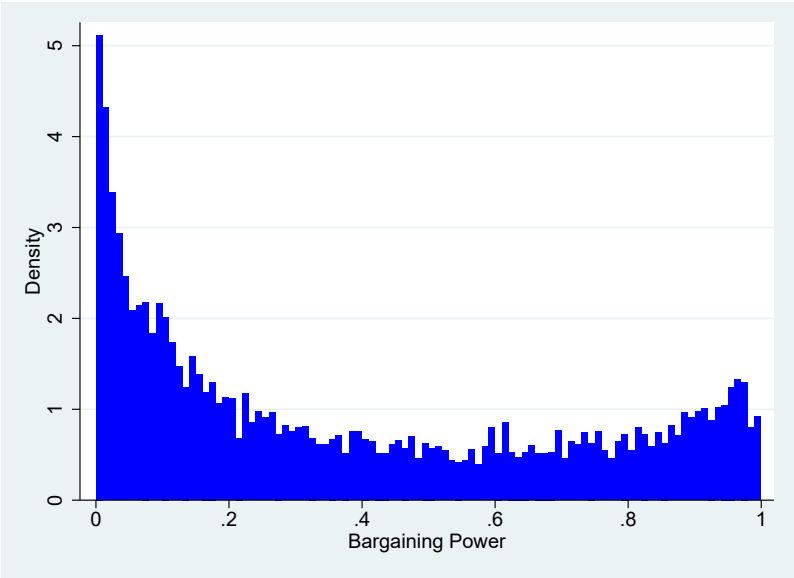

Figure 2.4. Overall Distribution of Bargaining Power: Marginal Cost=85% of Minimum Price

Figure 2.5 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 85% of minimum price.

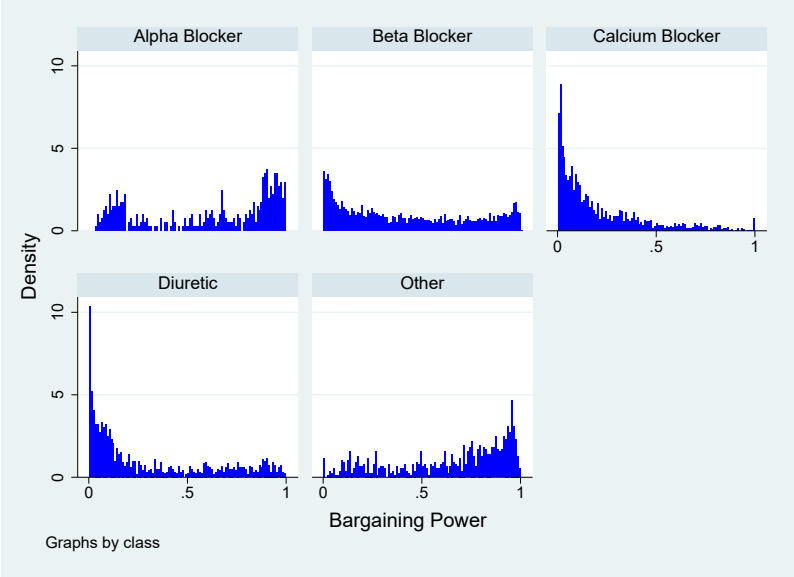

Figure 2.5. Overall Distribution of Bargaining Power by Class: Marginal Cost=85% of Minimum Price

Figure 2.5 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 85% of minimum price.

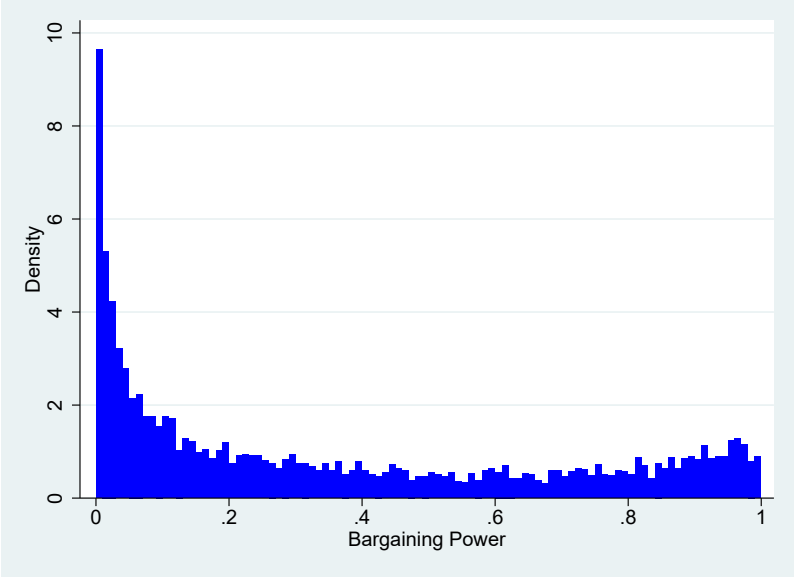

Figure 2.6. Overall Distribution of Bargaining Power: Marginal Cost=95% of Minimum Price

Figure 2.5 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 100% of minimum price.

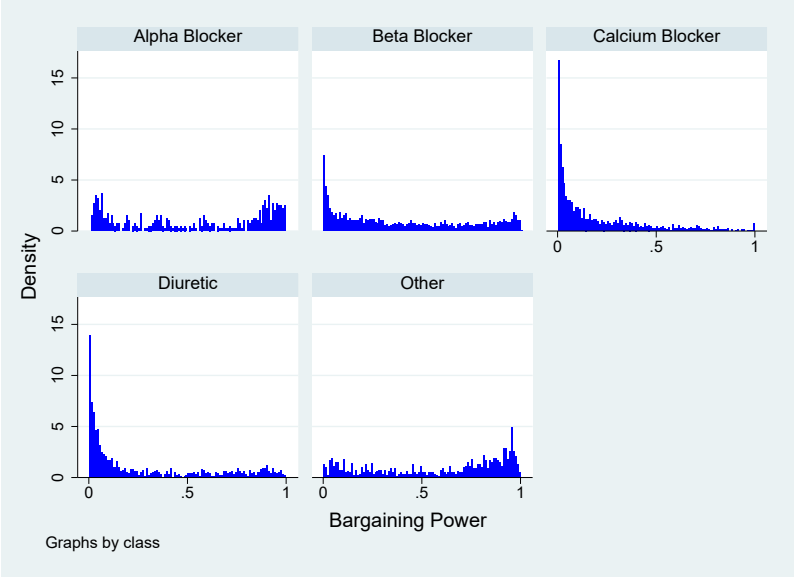

Figure 2.7. Overall Distribution of Bargaining Power by Class: Marginal Cost=95% of Minimum Price

Figure 2.5 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 95% of minimum price.

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 (2.1) captures this objective function as

$$\max_{p_{jct}} \underbrace{[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j) - d_{jct}]^{b_{jt}(c)}}_{Manufacturer\ Profits} \underbrace{[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}]^{b_{ct}(j)}}_{\text{Buyer Surplus}}, \tag{2.19}$$

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 (2.1) with regard to the negotiated price yields:

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

$$+b_{ct}(j)\left[\Pi_{ct}(\boldsymbol{p}_{ct}) - d_{cjt}\right]^{b_{ct}(j)-1}\left(\frac{\partial \Pi_{ct}(\boldsymbol{p}_{ct})}{\partial p_{jct}} - \frac{d_{cjt}}{\partial p_{jct}}\right)\left[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j)\right]^{b_{jt}(c)} = 0. \tag{2.20}$$

Dividing through Equation (2.2) 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:

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

$$+b_{ct}(j)\left(\frac{\partial \Pi_{ct}(\boldsymbol{p}_{ct})}{\partial p_{jct}} - \frac{d_{cjt}}{\partial p_{jct}}\right)\left[q_{jct}(\boldsymbol{p}_{ct})(p_{jct} - mc_j)\right] = 0. \tag{2.21}$$

Dividing Equation (2.3) by $q_{jct}(\boldsymbol{p}_{ct})$ gives:

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

$$+b_{ct}(j)\left(\frac{\partial \Pi_{ct}(\boldsymbol{p}_{ct})}{\partial p_{jct}}-\frac{d_{cjt}}{\partial p_{jct}}\right)\left[(p_{jct}-mc_j)\right]=0. \tag{2.22}$$

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:

$$q_{jct}(\boldsymbol{p}_{ct})(p_{jct}-mc_j) = \frac{b_{jt}(c)}{b_{ct}(j)}\left(\frac{\partial q_{jct}}{\partial p_{jct}}\frac{(p_{jct}-mc_j)}{q_{jct}(\boldsymbol{p}_{ct})}+1\right)\left[\Pi_{ct}(\boldsymbol{p}_{ct})-d_{cjt}\right]. \tag{2.23}$$

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

$$p_{jct} = mc_j + \frac{b_{jt}(c)}{b_{ct}(j)}\left(\frac{\partial q_{jct}}{\partial p_{jct}}\frac{(p_{jct}-mc_j)}{q_{jct}(\boldsymbol{p}_{ct})}+1\right)\frac{\left[\Pi_{ct}(\boldsymbol{p}_{ct})-d_{cjt}\right]}{q_{jct}(\boldsymbol{p}_{ct})}, \tag{2.24}$$

which is equivalent to Equation (2.2) (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 (2.18), 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 (2.17)) based on the change from a particular bargaining determinant (e.g., Quantity, Busi-

ness 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 (2.18) 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 (2.18) to generate a new surplus value (numerator of right-hand side Equation (2.18)), 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 (2.18) converge.

3. PRICE VARIATION IN THE RETAIL PHARMACEUTICAL MARKET: EVIDENCE FROM NEW HAMPSHIRE

Rising drug prices in the United States have become an important public health policy issue.[1] This policy debate has largely centered around rising list prices for brand-name drugs, particularly insulin.[2] Generic manufacturers have also faced price scrutiny.[3] However, debates about drug prices at the manufacturer level are only one aspect of the complicated supply chain a drug travels though before ultimately arriving to the patient. Even defining the price of a drug is unclear as a single drug can have at least four prices. There is the list, or cash, price: what an uninsured patient must pay a pharmacy when purchasing the drug. There is the wholesale price: the price the pharmacy pays the wholesaler or manufacturer. For insured patients, there is the out of pocket price: made up of copays, coinsurance, or deductibles. This is the price an insured patient pays the pharmacy when purchasing a drug. Additionally, there is the negotiated price: the price the insurance company pays the pharmacy when one of the insurance company's enrollees purchases the drug from that pharmacy.

Retail drug prices are further complicated by related, hidden prices such as rebates negotiated by Pharmacy Benefit Managers (PBMs) and premiums paid by insured patients to their insurance company. Furthermore, prices for branded drugs might behave differently than prices for branded drugs with multiple sellers. Both likely

[1]See https://www.nbcnews.com/health/health-care/no-end-sight-rising-drug-prices-study-finds-n1012181, for example.

[2]See https://www.businessinsider.com/insulin-price-increased-last-decade-chart-2019-9, for example.

[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)

behave differently than prices for generic drugs. This paper attempts to illuminate some of the mechanisms that drive negotiated price (price between pharmacies and insurance companies) and out of pocket price (price between pharmacies and insured patients). In particular, we are interested in the dispersion of negotiated and out of pocket prices that occur for the exact same drug.

Our study broadly fits in to the retail price dispersion literature first suggested by Salop and Stiglitz (1977). Many studies have empirically examined the Law of One Price in retail markets. Using scanner data some papers suggest that, in general, retail product prices do generally converge to a single price (DellaVigna and Gentzkow (2019); Hosken and Reiffen (2004)). Others have found the opposite. Kaplan and Menzio (2015) finds that identical goods can exhibit significant price variation and this price variation occurs both across stores and within the same store over time. These studies typically use only a small subset of retail goods. One exception is Hitsch et al. (2019). This study examines price data for more than 50,000 products and concludes that there is a substantial amount of price dispersion and that this price dispersion is heterogeneous across products. The authors also find that retail stores within the same retail chain exhibit less price variation than they do with stores of different chains.

These studies suggest that retail stores often do a poor job at optimizing prices based on local market demand conditions. MacDonald (2000) and Chevalier et al. (2003) add to this argument by showing that retail stores fail to respond to changes in positive demand shocks by altering prices. Adams and Williams (2019) shows that while consumer surplus increases when retailers fail to optimize prices for local markets, the effect on sellers is ambiguous. In some cases, setting more uniform prices across geographic markets can benefit the seller.

While the extent of price dispersion for general retail products might be uncertain, substantial variation in prices for health care has been well established. Cooper et al. (2019), for example, shows a high degree of price variation for identical hospital procedures across geographic markets. They find that the amount of hospital competition in a local market is a driving factor in establishing prices for a given medical procedure. Local supplier competition is a channel we will examine as well.

Competition also plays a role in prices physicians charge patients for consultations and outpatient procedures, though the results are perhaps mixed. Dunn (2012) shows that physicians in more concentrated markets charge commercially insured patients higher prices. The authors suggest that physician practice consolidation might be partially responsible for these higher prices. On the other hand, Gravelle et al. (2016) shows that physicians with more distant competitors tend to charge higher prices, a result seemingly in opposition to Dunn (2012). However, the setting in this study is the Australian nationalized health care system in which institutional characteristics could be quite different than the U.S. market for physician services. In one of the only papers examining retail pharmacy competition, Chen (2019) shows that retail pharmacies follow a similar pattern to physicians in the Dunn (2012) study. She finds that prices tend to be higher in markets with a higher concentration of pharmacies.

Our study is most closely related to those that examine the price dispersion for retail pharmaceuticals. Most of these studies examine price dispersion for the so-called cash price, the price a patient must pay a retail pharmacy to purchase the drug without using a third-party payer such as commercial or public insurance. This price may involve the use of discount coupons such as those from GoodRx. We refer to this price as the list price since it is the price a pharmacy charges a customer in the absence of a pre-negotiated rate. The first to look at this market was Sorsensen (2000) and Sorensen (2001). He found that cash paying patients faced different costs

across pharmacies for the same drug, with the average coefficient of variation being 0.22. Gellad et al. (2009) found price dispersion across geographic markets. Those cash-paying patients in poorer markets generally paid higher prices for retail pharmaceuticals. Bernstein et al. (2019) examined generic drugs specifically and found an even higher coefficient of variation than Sorsensen (2000) with an average coefficient of variation for generic drugs of 0.43. The medical literature has found high price variation for generic drugs, but pharmacy type and geography did not correlate to this price variation (Hauptman et al. (2017)). Using the same data source as our paper, Chen (2015) finds significant price dispersion for cash prices across retail pharmaceutical markets in New Hampshire.

While it is natural to focus on uninsured patients since they face the highest costs, it is important to remember that 91.2% of Americans have health insurance coverage, and, of those, over two-thirds are covered by commercial insurance.[4] Therefore, it is important to study price dispersion for these consumers as well, but this has been hampered due to a lack of data availability. Few studies have examined the dispersion of other prices in this market. Several papers have attempted to study the dispersion of wholesale prices, the price retail pharmacies pay to the wholesaler or manufacturer. Cook (2000) finds that, for branded drugs, hospitals and health maintenance organizations are able to achieve higher price discounts than retail pharmacies since they are able to influence the prescribing behavior of physicians. Ellison and Snyder (2010) show a similar result. The authors find that retail pharmacies are unable to achieve wholesale discounts for drugs with monopoly sellers and only modest discounts for drugs with competing sellers. Einav et al. (2018) examines the price dispersion of out of pocket prices for patients on Medicare Part D plans. This study finds that

[4]According to 2017 U.S. Census data.

patients' out of pocket prices vary substantially depending on their particular Part D plan.

In addition to Einav et al. (2018), several papers have examined public insurance such as Medicaid and Medicare Part D plans on retail drug prices. Duggan and Scott Mortan (2006) shows that drugs with high Medicaid utilization rates increase the commercial retail prices for that drug. Duggan and Scott Morton (2010) and Dranove et al. (2007) find that Medicare Part D plans can reduce drug costs for both generic and branded drugs through the use of formularies.

To our knowledge, no other study has examined the price dispersion of negotiated prices between commercial insurers/PBMs and retail pharmacies. Knowledge of how much price variation these insurers face can help quantify the limits of their ability to obtain bargaining surplus from retail pharmacies. Achieving lower negotiated prices could allow insurers to pass that savings on the their enrolled patients. It is unclear, however, if insurers would alter their enrollee's out of pocket prices even if they were able to obtain low negotiated rates. Since we observe both of these prices, we can provide insight in to this question.

We contribute to the literature by providing insights into bargained prices between retail pharmacies and insurers (as well as out of pocket costs for covered patients). These insights can increase our understanding of which factors matter in determining negotiated prices and out of pocket costs. Additionally, by combining our data with Medicare Part D data, we can examine differences in negotiated rates and, by extension, bargaining ability between commercial plans and Part D plans.

We use a database that contains all pharmacy claims data for all health insurers and patients in New Hampshire from 2011 through 2017. This database reports both the negotiated and out of pocket price for every retail pharmacy claim made in this period as well as other information about the claim. Using the posted cash

price to measure price dispersion can be problematic since those sales may not have actually occurred (Ghose and Yao (2011)). Since our data contain prices for actual transactions we avoid this issue. We describe the data in more detail and provide descriptive statistics about price variation, price distributions, prices over time, and competition among pharmacies in the next section. Section 3 presents our initial regression results and discuses those results. We conclude in Section 4.

3.1 Data Sources and Descriptives

3.1.1 Data Sources

In 2005, the state of New Hampshire, via the New Hampshire Insurance Department and the New Hampshire Department of Health and Human Services, wanted to make healthcare information more transparent for insurers, employers, providers, patients, and state agencies. The state launched one of the first public claims databases in the United States known as the "All-Payer Claims Database."[5] In New Hampshire private, commercial health insurers must submit their health care claims data to the state.[6] These commercial insurance claims cover medical, dental, and pharmacy services.

Though New Hampshire was one of the first, there are currently 28 states with some form of an All-Payer Claims Database (APCD).[7] Of these 28 APCDs, 18 are legislated by the state, including the New Hampshire APCD, five are state legislated

[5]A comprehensive case study of this database conducted by the deBeaumont Foundation can be located here: https://www.astho.org/Health-Systems-Transformation/Medicaid-and-Public-Health-Partnerships/Case-Studies/New-Hampshire-All-Payer-Claims-Database/.
[6]The New Hampshire Insurance Department has the legal authority to enforce this regulation.
[7]A study by the RAND corporation was commissioned by the state of Indiana to study these APCDs. For more information, see: https://employersforumindiana.org/media/2020/02/APCD-White-Paper-by-Employers-Forum-of-Indiana-2-9-20.pdf.

but not yet implemented, and five are implemented by volunteer organizations rather than the state.

In New Hampshire, information on average prices for certain medial and dental services and insurers can be accessed by anyone.[8] However, information on pharmacy services are not available. Additionally, the non-public use pharmacy data we use in this paper is much more granular that what is available to the public. The data for this paper covers the universe of commercial pharmacy claims for the years 2011 through 2017 in the state of New Hampshire. We remove claims from patients aged 65 and older to avoid issues with Medicare supplemental insurance. We also remove insurers with fewer than 500 members to avoid claims with very small insurance companies.

Our claims data provide information on insurers, patients, pharmacy providers, drugs, and prices at the individual claim level as well as information related to the commercial health insurance provider. We observe the name of the insurer, the type of insurance (hmo, ppo, etc.), and insurance plan information. Patient information includes age, sex, state of residence, and relationship to the subscriber (beneficiary, spouse, or dependant). Provider, which in this case are retail pharmacies, information includes the pharmacy name, national provider identifier (NPI), and parent company. We match these pharmacies to addresses using their NPI which allows us to use ArcGIS software to determine the distance between pharmacies. Variables related to the drug include drug name, national drug code (NDC), dosage, quantity by units, and an indicator for if the drug is generic or branded. We use the NDC to match the drug to its manufacturer (or wholesaler), its formulation, and its dosage.

National drug codes (NDCs) provide a convenient way to isolate products. The NDC is an eleven digit number that identifies the labeler, product, and package. The

[8]See https://nhhealthcost.nh.gov/costs/select.

labeler is the firm that manufactures or distributes the drug. This is the firm that sells the drug to the pharmacies in the wholesale market. The product component of the NDC identifies the molecule, specific strength of the active ingredient, dosage form, and formulation for the drug. The package component identifies the package form and size, such as the total number of pills in a bottle. When we refer to a drug, product, or molecule in this paper we mean a specific NDC of that drug. For example, a 500mg tablet of amoxicillin manufactured by Sandoz is a completely different product that a 500mg amoxicillin tablet manufactured by Teva. Similarly, a 500mg tablet of amoxicillin manufactured by Sandoz is a completely different product than a 250mg tablet of amoxicillin manufactured by Sandoz. This allows us to avoid any price variation that would be caused by differences in manufacturer, dosage amount, package size, formulation, etc. Therefore, any price variation we do see is despite products being *exactly* identical.

We have rich information on the prices for each drug claim. First, we observe the list price. The list price is the price the pharmacy sets for uninsured patients. Next, we see the negotiated price, which is the price an insurance company reimburses the pharmacy for a claim. This price is negotiated between the insurance company and the pharmacy. We also observe patients out of pocket expenses. These include co-payments, coinsurance, and deductible payments. If a patient does face an out of pocket expense, it will typically just be one of these types of payments; a patient will pay a copay or coinsurance but not both. For this reason, we create a new variable called out of pocket price which is a sum of these various types of patient expenses. We create one last price variable called price received. This is the total payment that the pharmacy received for dispensing the drug. It is simply the sum of the negotiated price (that the pharmacy receives from the insurer) and the out of pocket price (that the pharmacy receives from the patient).

Figure 3.1.1 shows graphically the relationship between agents in the pharmaceutical industry and the various prices among them. The green price arrows represent the prices described above that we observe in the data. The red arrows are other prices that we do not observe. These include wholesale prices that the pharmacies pay to wholesalers or manufacturers, rebates negotiated by Pharmacy Benefit Managers (PBMs) on behalf of insurers (typically only for branded drugs), and insurance premiums paid by patients to insurers. Despite not observing these, the prices we do observe allow us to form a complete picture of the price relationships between retail pharmacies, patients, and third party insurers.

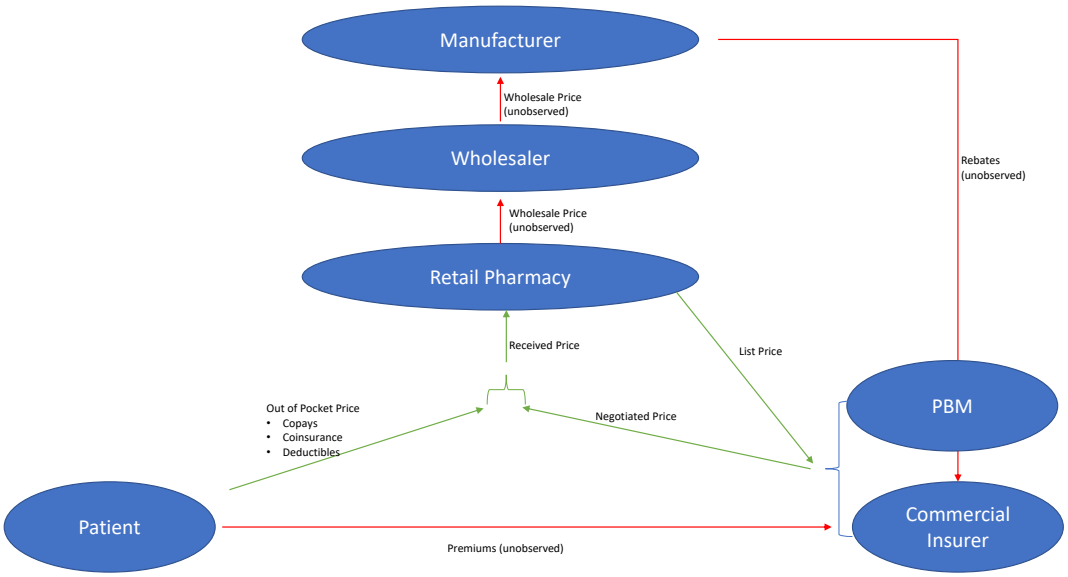

Figure 3.1. Pharmaceutical Industry: Observed and Unobserved Prices

3.1.2 Price Variation

We begin by measuring the price variation for several drug prices in our data. We define a drug as a specific National Drug Code (NDC). It is important to note that a NDC specifies both a dosage and a manufacturer. For example, when we reference a drug by name we are actually referring to not only that drug but also a specific dosage and a specific manufacturer. Because of this, any price variation that is present in the data will not be due to differences in dosage amounts or quality differences that originate from the manufacturer.

We measure price variation by using the coefficient of variation. This is simply the standard deviation of a price divided by the mean of that price. So if the price variation (PV) of a drug is equal to one, that means the standard deviation of its price is the same as the mean. We are primarily interested in how prices vary across pharmacies and insurers so we limit our descriptive statistics to a single year (2017) in order to minimize price changes over time affecting the PV.

We measure the PV for two different prices. The first is negotiated price, which is the price insurance companies reimburse pharmacies for a drug claim. This price is negotiated between the pharmacy and the commercial insurer. The second price we examine is the out of pocket price. This is the price patients face when they purchase a drug from a pharmacy, but use their insurance. It might include copays, coinsurance, or deductable payments. This price has implications for patient welfare.

Since we have hundreds of different drugs in our data it is not feasible to report price variation for every drug. We report price variation summary statistics for ten drugs, one branded and nine generic. Table 3.1 shows the price variation of negotiated price for these drugs across several different dimensions. Table 3.2 shows the same price variations but for the out of pocket price.

Table 3.1.
Price Variation - Negotiated Price

	Suboxone (Branded)	Amoxicillin	Azithromycin	Cyclobenzaprine HCL	Fluticasone Propionate	Hydrochloro-thiazide	Lisinopril	Lorazepam	Omeprazole	Oxycodone/ Acetaminophen
PV across pharmacies within zip code (Avg)	0.192	0.600	0.728	0.777	0.468	0.496	0.774	1.010	0.843	0.380
BY CHAIN										
CVS	0.260	0.749	0.888	0.826	0.556	.	0.875	1.132	1.072	0.518
Hannaford	0.058	0.572	.	.	0.553	.	0.740	0.724	0.927	0.516
Maxi Drug	0.231	0.646	0.279	.	0.453	1.081	.	0.872	.	0.092
Rite Aid	0.219	0.477	0.769	0.378	.	.	.	.	.	.
Victory Distributors	0.635	0.614	.	.	0.511	.	0.589	5.025	0.814	0.095
Walgreens	0.251	.	.	.	0.503	0.667	0.795	.	1.188	.
Walmart	0.290	.	0.599	1.306	.	0.260	.	.	.	.
Independent (Avg)	0.185	1.485	0.601	1.169	0.855	1.322	0.666	0.782	0.932	0.825
Within pharmacy across insurers (Avg)	0.290	0.604	0.698	0.834	0.510	0.544	0.797	0.871	0.735	0.313
Within insurer across pharmacies (Avg)	0.044	0.286	0.192	0.361	0.184	0.426	0.406	0.767	0.304	0.226
BY INSURER										
Caremark, LLC	0.078	0.490	0.676	0.597	0.336	0.213	0.549	0.564	0.760	0.695
Express Scripts	0.023	0.263	0.113	0.495	0.339	0.327	0.404	3.292	0.466	0.087
Harvard Pilgrim	0.043	0.529	0.328	0.272	0.189	0.765	0.207	0.367	0.315	0.228
Minuteman Health	0.023	0.279	0.004	0.425	0.056	0.129	0.484	0.354	0.204	0.059
Symphonix	0.055	0.216	0.395	0.227	0.419	0.539	0.590	0.359	0.342	.
Tufts Benefit Administrators	0.004	0.140	0.031	0.203	0.077	0.248	0.310	0.212	0.206	.
Tufts Health Freedom Insurance	0.003	0.140	0.031	0.176	0.071	0.226	0.226	0.209	0.163	.
UnitedHealthcare	0.053	0.050	0.095	0.500	0.039	.	0.143	0.611	0.066	.
Wellcare	0.111	0.464	0.056	0.353	0.127	0.962	0.737	0.940	0.217	0.060

Table 3.1 shows price variation for negotiated price for year 2017. Price variation is measured at the NDC level which removes potential variation due to different manufacturers or different dosages.

Table 3.2.
Price Variation - Out of Pocket Price

	Suboxone (Branded)	Amoxicillin	Azithromycin	Cyclobenzaprine HCL	Fluticasone Propionate	Hydrochloro-thiazide	Lisinopril	Lorazepam	Omeprazole	Oxycodone/ Acetaminophen
PV across pharmacies within zip code (Avg)	1.801	0.769	0.838	1.138	0.727	0.771	0.934	1.213	1.074	0.606
BY CHAIN										
CVS	1.632	0.907	0.864	1.202	0.817	.	1.025	1.232	1.373	0.840
Hannaford	1.547	0.810	.	.	0.878	.	1.020	0.922	1.337	1.011
Maxi Drug	1.754	0.835	0.612	.	0.575	0.973	.	0.872	.	0.762
Rite Aid	1.746	0.807	0.531	1.939	0.569	.	.	.	.	.
Victory Distributors	1.761	0.710	.	.	0.847	.	0.810	5.723	1.186	0.333
Walgreens	1.761	.	.	.	0.891	0.937	0.923	.	0.968	.
Walmart	1.839	.	0.850	1.179	.	0.906	.	.	.	.
Independent (Avg)	1.773	0.602	0.829	1.187	0.842	1.388	0.826	1.116	1.625	1.011
Within pharmacy across insurers (Avg)	1.097	0.806	0.873	0.883	0.808	0.825	0.964	0.867	0.920	0.618
Within insurer across pharmacies (Avg)	0.989	0.781	0.674	0.725	0.422	0.957	0.879	1.420	0.732	0.477
BY INSURER										
Caremark, LLC	0.976	0.545	0.820	0.698	0.346	0.390	0.616	0.603	0.942	1.051
Express Scripts	0.858	0.305	0.215	0.758	0.300	0.422	0.615	4.832	0.507	0.359
Harvard Pilgrim	1.267	0.370	0.244	0.447	0.338	0.976	0.281	0.452	0.433	0.284
Minuteman Health	1.328	0.422	0.067	0.526	0.269	0.129	0.458	0.422	0.299	0.206
Symphonix	1.483	1.636	1.002	2.013	1.073	1.786	1.549	0.930	1.429	.
Tufts Benefit Administrators	0.591	0.165	0.056	0.280	0.118	0.254	0.310	0.212	0.271	.
Tufts Health Freedom Insurance	0.451	0.155	0.261	0.209	0.113	0.545	0.636	0.243	0.390	.
UnitedHealthcare	1.144	0.176	0.243	0.549	0.156	.	0.143	0.707	0.247	.
Wellcare	0.801	3.259	3.155	1.042	1.083	3.152	3.305	4.377	2.066	0.484

Table 3.2 shows price variation for out of pocket price for year 2017. Price variation is measured at the NDC level which removes potential variation due to different manufacturers or different dosages.

This first row in these tables shows the average price variation across all retail pharmacies within a zip code. This shows the price variation among pharmacies while removing potential variation in geography. The next section shows the price variation within a particular large pharmacy chain (or an average across independent pharmacies). This shows the variation across geography while removing potential variation among pharmacy chains. The next row, within pharmacy across insurers, shows the average price variation across different insurance payers but within the same exact retail pharmacy locations. This removes both geographic variation as well as variation across pharmacies, leaving only variation among commercial insurance payers. The next row, within insurer across pharmacies, holds the third party insurance payer constant and shows price variation across all retail pharmacies. The last section breaks this down by the specific third party insurance payer.

Tables 3.1 and 3.2 contain an abundance of price variation information. Here, we will try to present some general takeaways and conclusions from this price variation information, with the caveat that these conclusions are based on only a sample of NDCs, though those NDCs we include in the price variation tables are the most commonly sold NDCs.

First, variation in negotiated price across zip codes is much higher for generic drugs than branded. This is consistent with the point raised by Lakdawalla and Yin (2015) that manufacturers of branded drugs with no or few substitutes are able to extract all or most of the available surplus leaving little surplus to bargain over for the pharmacy and insurer. Similarly, we can see that the negotiated price variation is much higher for generics than branded drugs across most of the specific pharmacy chains. This is also true for independent pharmacies. Price variation among independent pharmacies seems to be somewhat lower than large chains for most of the drugs.

Interestingly, for all drugs, the negotiated price variation within a pharmacy and across insurers is higher than within an insurer across pharmacies. This suggests that the insurer might matter more than the pharmacy for determining negotiated prices. As before, variation for generic drugs is much higher than for the branded drug.

The last section shows the variation in negotiated prices among each insurer. As before, variation is much higher for generic drugs than branded.

As seen in Table 3.2, the pattern of price variation among branded and generic drugs is generally the opposite for out of pocket costs. Here, the branded drug exhibits higher out of pocket price variation than all of the generics across pharmacies within a zip code. Likewise, the PV for the branded drug is much higher than for the generic drugs in all of the major retail pharmacy chains as well as independent pharmacies. These high PVs for the branded drug are also very consistently high across each of the chains. The within pharmacy PV vs within insurer PV is more similar for out of pocket prices (both branded and generics) than it was for negotiated prices. This indicates that insurer competition might not affect out of pocket prices as strongly as it affects negotiated prices. Most insurance companies tend to have relatively stable out of pocket prices, at least for generic drugs, though there are exceptions such as Symphonix that have high variation in out of pocket prices across all of the drugs in this sample. The likely explanation for larger out of pocket price variation for branded drugs as compared to generics are higher overall patient costs for branded drugs and different tier placement on the insurance company's formularies.

The three primary takeaways from the price variation descriptive statistics are: first, variation in negotiated price is larger for generics than branded drugs, second, for generics, the variation in negotiated prices within pharmacies and across insurers is larger than within insurers and across pharmacies, and, third, these patterns between generic and branded drugs are generally flipped for out of pocket prices.

3.1.3 Price Distributions

For a more visual description of these price variations, we present the distribution of negotiated prices, as well as list prices, for the ten most popular branded and generic NDCs in the year 2017. Recall that list price is the price set by the pharmacy that an uninsured patient would face. Though list prices are set at the pharmacy level, it is likely the case, especially for branded drugs, that these list prices are a direct result of the manufacturer's suggested retail price. Figure 3.1.3 shows the distribution of list prices for the ten most popular branded NDCs. Half of these ten drugs exhibit virtually no dispersion in list prices across pharmacies. It is likely that for these drugs almost all surplus is captured by the manufacturer.

List prices for generics, on the other hand, exhibit a great deal more dispersion as shown in Figure 3.1.3. Remember that these drugs represent only a single NDC so the dispersion in these list prices are for a single dosage, package amount, and manufacturer. Thus, this dispersion in list price is showing the difference in market conditions across geography and pharmacy chains.

Negotiated prices for branded drugs track list prices closely, as shown by comparing Figure 3.1.3 to Figure 3.1.3. This fact will also be confirmed later in the Results section. Like list prices, negotiated prices for branded drugs are typically not very dispersed. Again, this is consistent with the pharmacy and insurer having little available surplus to bargain over.

Figure 3.1.3 shows the distribution of negotiated prices for the top ten (by volume) generic NDCs. Like list prices, negotiated prices for generics are widely dispersed for most drugs. Unlike for branded drugs, the negotiated prices for generics do not closely track their list price.

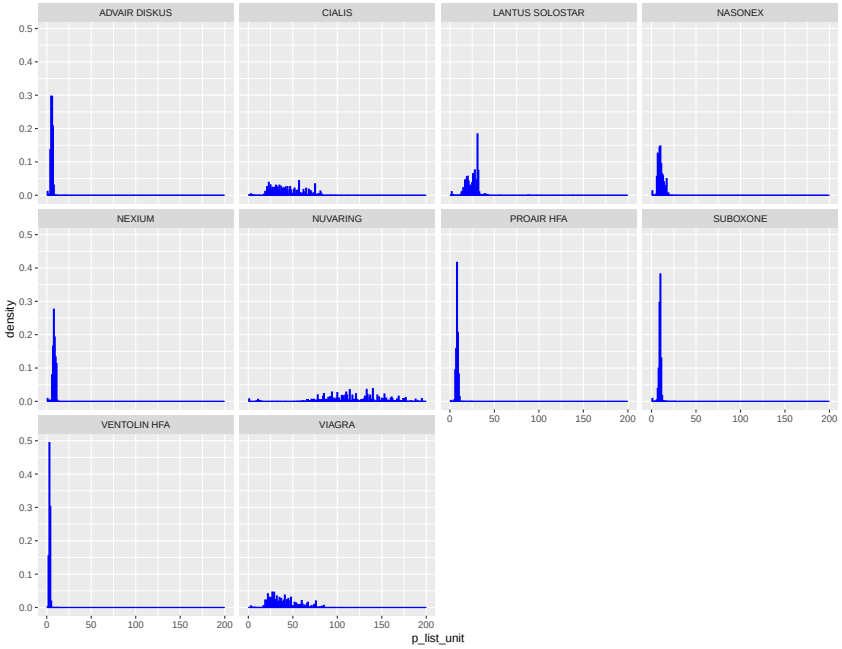

Figure 3.2. List Price Distribution: Branded

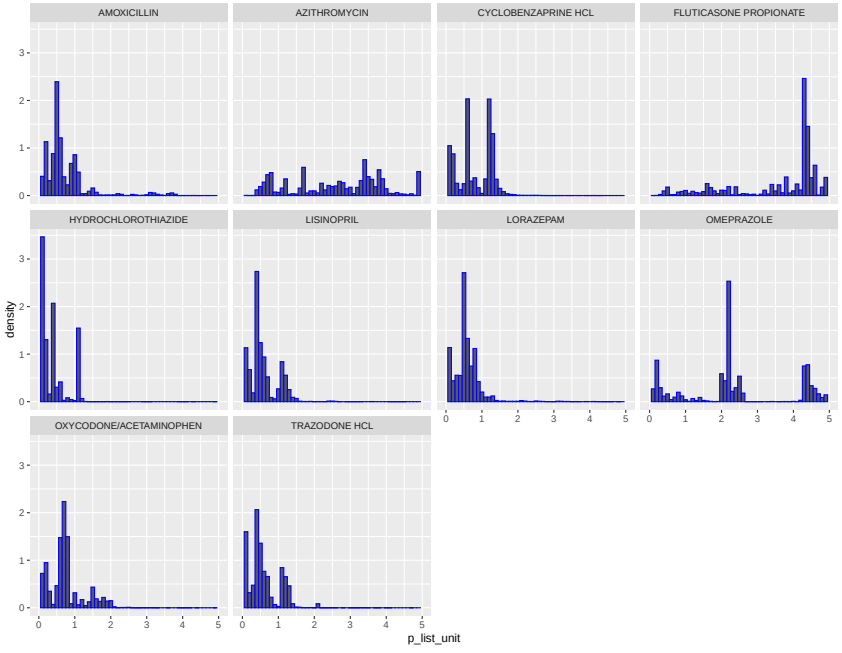

Figure 3.3. List Price Distribution: Generic

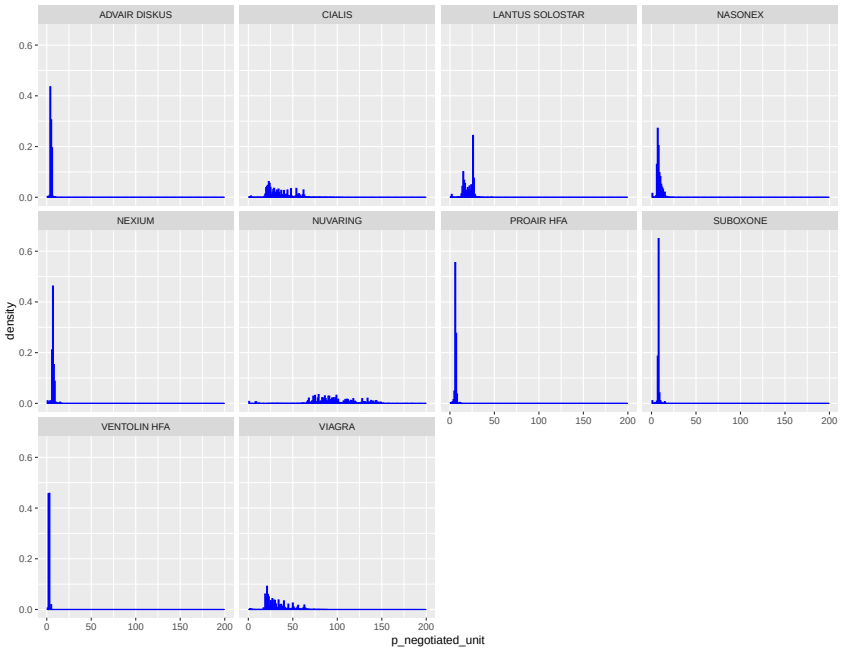

Figure 3.4. Negotiated Price Distribution: Branded

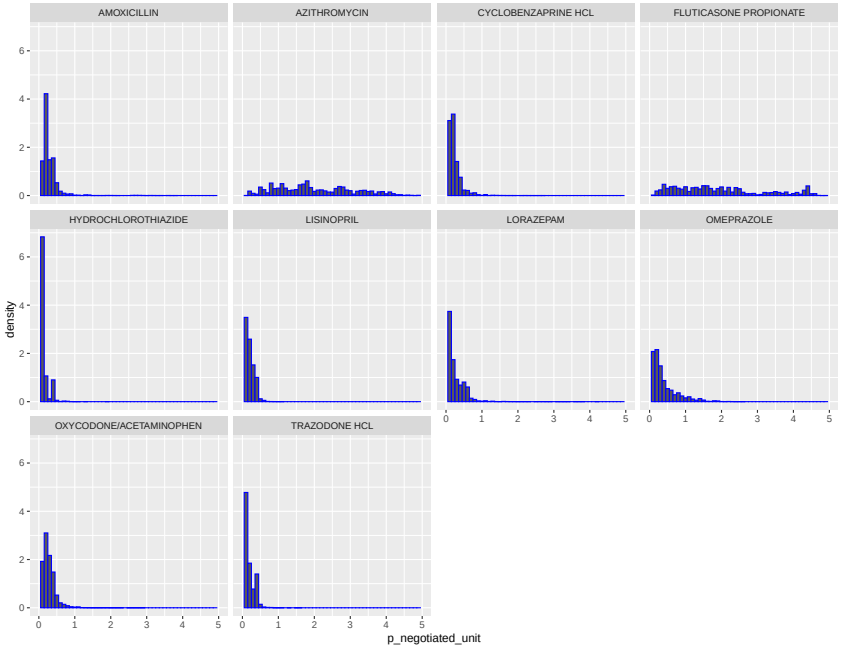

Figure 3.5. Negotiated Price Distribution: Generic

3.1.4 Prices over Time

Thus far all price variation and summary statistics have been for one year only (2017). It is also important to look at how prices have changed over time. To examine this, we average prices for all branded and all generic drugs in order to look at overall trends. Drug specific time trends for a sample of generic and branded drugs are presented in the appendix. All prices are adjusted for inflation and are reported in 2018 dollars.

Figure 3.1.4 shows average prices over time for branded drugs. From 2010 to 2017 the average list price of a branded drug increased from about $ 15 to $25. This provides some support for the general idea that pharmaceutical list prices have increased significantly in recent years. It is clear that negotiated prices have tracked list prices closely over time, though the spread between the two has increased somewhat in later years. Interestingly, patients' out of pocket prices have actually decreased, on average, over time.

Figure 3.1.4 shows average prices over time for generic drugs. Unlike for branded drugs, list prices have not significantly increased over time, though there is some volatility in the list price. Also unlike branded drugs, negotiated prices do not seem to closely track the list price for generic drugs. Negotiated prices for generic drugs have significantly decreased over time for generics. Similar to branded drugs, out of pocket prices for generics have steadily decreased over time.

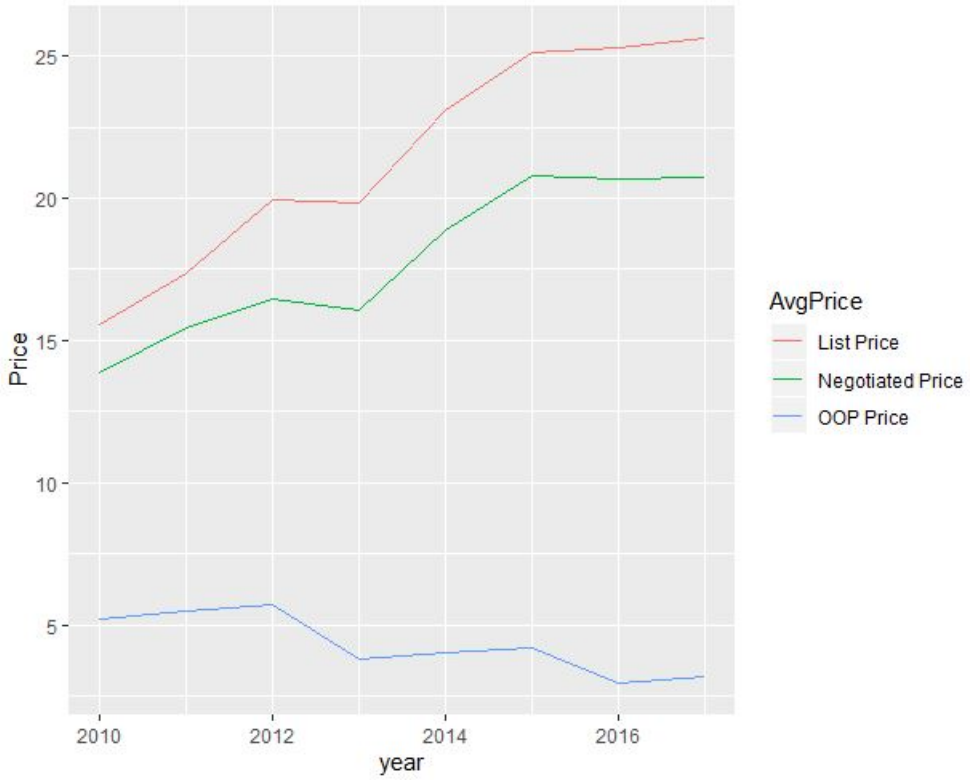

Figure 3.6. Prices over Time: Branded

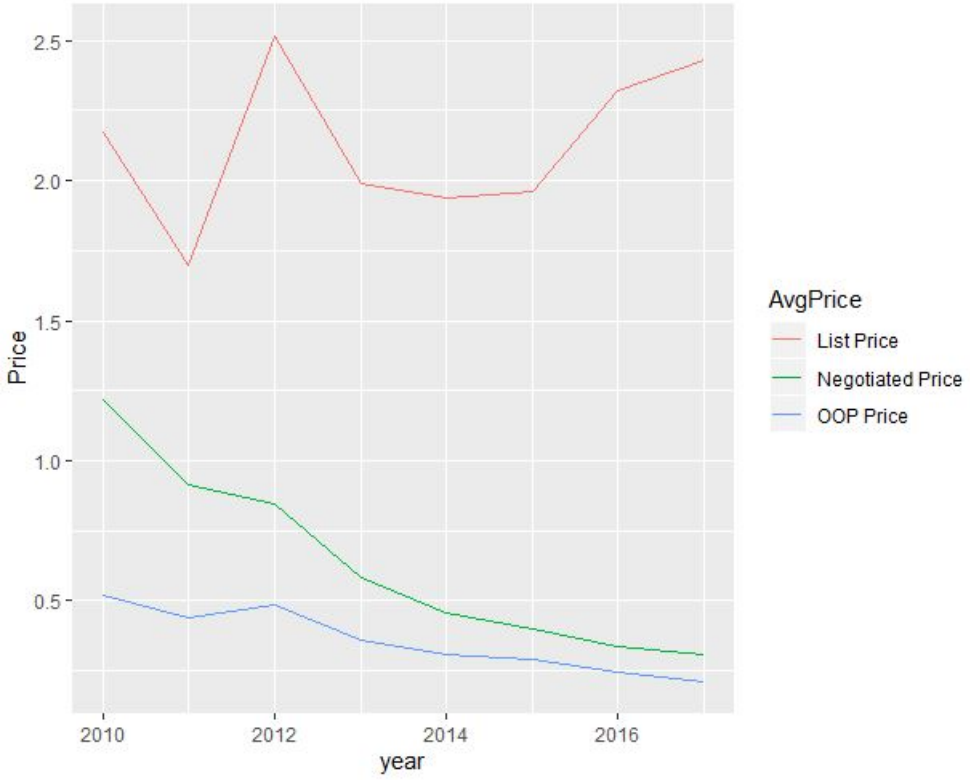

Figure 3.7. Prices over Time: Generic

3.1.5 Competition

The geographic location of physical retail pharmacy locations could be an important factor in determining negotiated prices. Pharmacies and chains in more convenient locations, or those without other pharmacies close by, might be able to command higher negotiated prices from insurers. There are many ways to measure competition in the context of the health-care industry. One could construct a Herfindahl-Hirschman Index (HHI) based on market shares (Gowrisankaran et al. (2015)). Other work has used density measures such as the number of physicians per capita (Bradford and Martin (2000); Richardson et al. (2006), or travel distance (Dunn (2012); Gravelle et al. (2016)). These studies are all focused on hospitals or physicians since lack of pharmacy data makes measuring pharmacy competition difficult. One exception that uses travel distance between pharmacies is Chen (2019). In our study we choose a density metric to measure pharmacy competition. We count the number of competitor pharmacies in a given radius (measured in miles) from a given pharmacy.

To measure geographic competition among retail pharmacies we match the pharmacy National Provider Identifier (NPI) with that pharmacy's street address. We then input the street addresses into ArcGIS software to plot a GPS location. Then, using that same software, we count the number of locations within a certain radius from each pharmacy. That becomes the value of the competition variable for that pharmacy. A map of all retail pharmacy locations in New Hampshire is shows in Figure 3.1.5.

Since it is not clear what the appropriate radius is to measure retail pharmacy competition, we use several different radii to measure competition. We chose two miles, five miles, ten miles, and twenty-five miles as potential measures of geographic competition. Ultimately, the choice of radius made little difference in terms of the sign

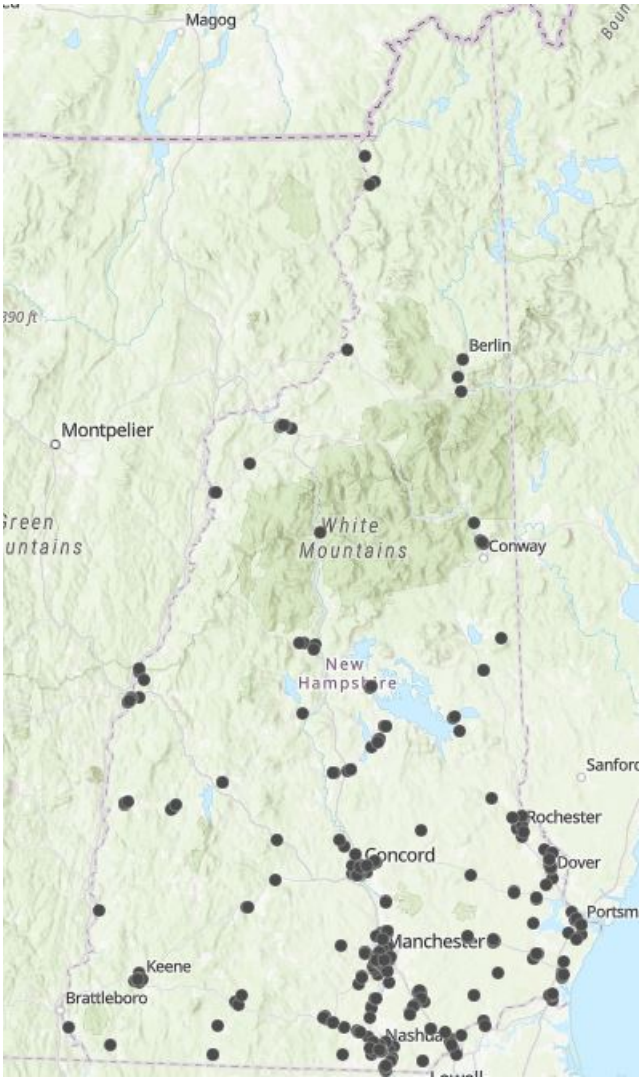

Figure 3.8. Retail Pharmacies in New Hampshire

or magnitude of the coefficient on the competition variable in our regressions. In the main paper we will use the two mile and ten mile competition measure. The density of these competition measure is shown in Figure 3.1.5 and Figure 3.1.5. For the two mile competition measure, most pharmacies have between one and ten competitors, with three being most common, but there are a significant number of pharmacies who are local monopolies at this distance measure. For the ten mile competition measure, most pharmacies have between one and thirty-five competitors. Densities for the other competition measures are shown in the appendix.

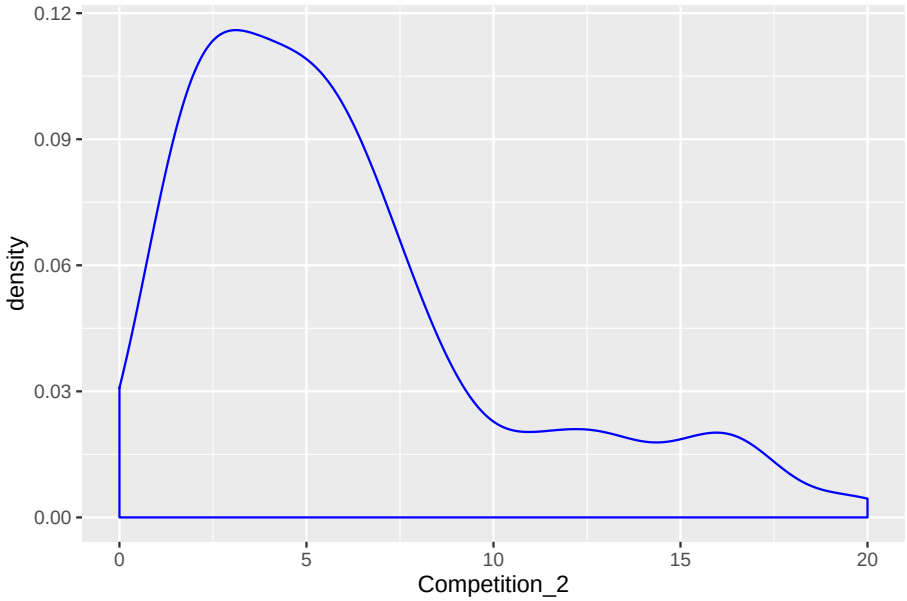

Figure 3.9. Density of Retail Pharmacy Competition - Two Miles

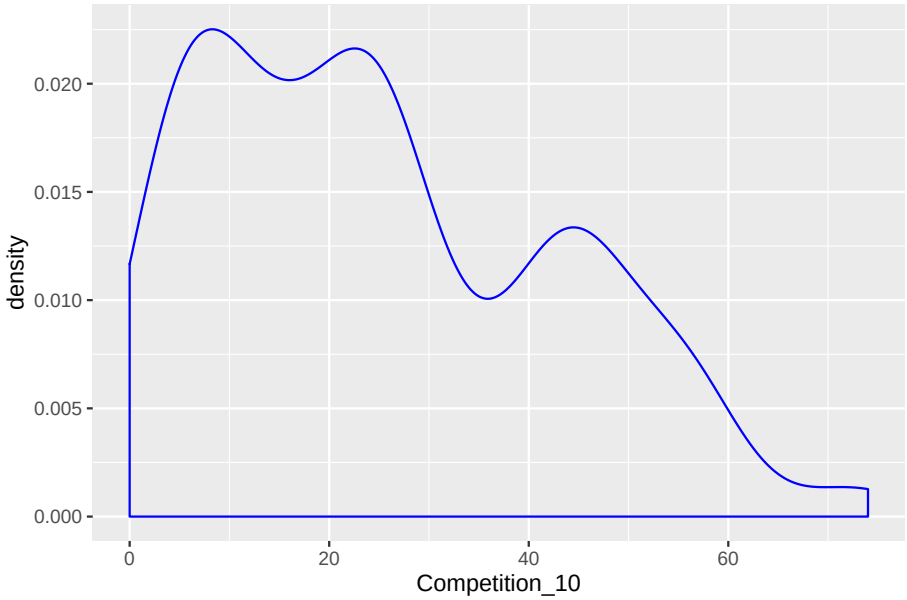

Figure 3.10. Density of Retail Pharmacy Competition - Ten Miles

3.2 Results and Discussion

To better understand the effects of several explanatory variables on negotiated prices we run an OLS regression of negotiated price on these explanatory variables. We expect many of these variables to have some effect on negotiated prices. First, we consider the drug's list price. We measure this as the log of the list price per unit of the drug. Second, for generic drugs, we expect the number of manufacturers of that drug overall, as well as the number of manufacturers that sell that drug in a particular pharmacy, to be important. Third, we use the number of insurers that cover a particular NDC. Fourth, we consider the number of enrollees of an insurer as a measure of insurer size. Last, we consider the number of competitor pharmacies at the two and ten-mile levels.

Table 3.3 through Table 3.5 report the results of these regressions. In Table 3.3 we consider the negotiated price to be the price per unit of the drug, in other words the amount of the negotiated price for the claim is divided by the quantity (in units) of the drug. In Table 3.4 we do not adjust negotiated price, so this is just the negotiated price of the overall claim. In Table 3.5 we use the negotiated price per day supply of the drug. For each regression we also include year, drug, zip code, insurer, and pharmacy chain fixed effects. We also do separate regressions for branded and generic drugs. Despite the different measures of negotiated price, generally the results are the same.

As expected, the list price is always positively and meaningfully associated with negotiated price regardless of specification. The magnitude of the effect is roughly twice as high for branded drugs rather than generics. The overall number of manufacturers (for generic drugs) has a small effect on negotiated price. In the first specification, the effect is positive, while in the other two specifications it is negative. The number of manufacturers for a drug sold in a particular pharmacy has a stronger

Table 3.3.
Negotiated Price - Price per Unit

	Dependent variable:			
	lnp_negotiated_unit			
	Branded 2	Generic 2	Branded 10	Generic 10
lnp_list_unit	0.691***	0.291***	0.691***	0.291***
	(0.001)	(0.001)	(0.001)	(0.001)
n_manuf_full		0.002***		0.002***
		(0.0004)		(0.0004)
n_manuf_pharm		0.006***		0.006***
		(0.001)		(0.001)
n_insurance_ndc	0.005***	0.008***	0.005***	0.008***
	(0.0001)	(0.0004)	(0.0001)	(0.0004)
n_enrollees_10000	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
n_pharm_2	0.0005***	0.005***		
	(0.0001)	(0.0004)		
n_pharm_10			−0.0002***	0.002***
			(0.0001)	(0.0002)
Constant	0.159***	−1.484***	0.169***	−1.545***
	(0.005)	(0.022)	(0.006)	(0.024)
Year FE	Yes	Yes	Yes	Yes
Drug FE	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes
Chain FE	Yes	Yes	Yes	Yes
Pharmacy FE	No	No	No	No
Observations	850,736	1,031,574	850,736	1,031,574
R^2	0.978	0.814	0.978	0.814
Adjusted R^2	0.978	0.814	0.978	0.814
Residual Std. Error	0.171 (df = 850607)	0.571 (df = 1031443)	0.171 (df = 850607)	0.571 (df = 1031443)
F Statistic	301,732.100*** (df = 128; 850607)	34,729.590*** (df = 130; 1031443)	301,726.300*** (df = 128; 850607)	34,723.960*** (df = 130; 1031443)

*p<0.1; **p<0.05; ***p<0.01

Table 3.4.
Negotiated Price - Price per Claim

	Dependent variable:			
	lnp_negotiated			
	Branded 2	Generic 2	Branded 10	Generic 10
lnp_list	0.936***	0.369***	0.936***	0.369***
	(0.0005)	(0.001)	(0.0005)	(0.001)
n_manuf_full		−0.001***		−0.001***
		(0.0004)		(0.0004)
n_manuf_pharm		0.009***		0.009***
		(0.001)		(0.001)
n_insurance_ndc	−0.001***	0.009***	−0.001***	0.009***
	(0.0001)	(0.0004)	(0.0001)	(0.0004)
n_enrollees_10000	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
n_pharm_2	0.001***	0.004***		
	(0.0001)	(0.0004)		
n_pharm_10			−0.0003***	0.001***
			(0.0001)	(0.0002)
Constant	0.268***	0.561***	0.280***	0.540***
	(0.005)	(0.023)	(0.006)	(0.024)
Year FE	Yes	Yes	Yes	Yes
Drug FE	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes
Chain FE	Yes	Yes	Yes	Yes
Pharmacy FE	No	No	No	No
Observations	850,736	1,031,574	850,736	1,031,574
R^2	0.958	0.613	0.958	0.613
Adjusted R^2	0.958	0.613	0.958	0.613
Residual Std. Error	0.176 (df = 850607)	0.577 (df = 1031443)	0.176 (df = 850607)	0.578 (df = 1031443)
F Statistic	149,971.100*** (df = 128; 850607)	12,581.360*** (df = 130; 1031443)	149,965.400*** (df = 128; 850607)	12,578.870*** (df = 130; 1031443)

*p<0.1; **p<0.05; ***p<0.01

Table 3.5.
Negotiated Price - Days Supply

	Dependent variable:			
	lnp_negotiated_day			
	Branded 2	Generic 2	Branded 10	Generic 10
lnp_list_day	0.978***	0.443***	0.978***	0.443***
	(0.0004)	(0.001)	(0.0004)	(0.001)
n_manuf_full		−0.004***		−0.004***
		(0.0005)		(0.0005)
n_manuf_pharm		0.003***		0.003***
		(0.001)		(0.001)
n_insurance_ndc	−0.001***	0.006***	−0.001***	0.006***
	(0.0001)	(0.0004)	(0.0001)	(0.0004)
n_enrollees_10000	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
n_pharm_2	0.0005***	0.004***		
	(0.0001)	(0.0004)		
n_pharm_10			−0.0003***	0.002***
			(0.0001)	(0.0002)
Constant	−0.038***	−0.633***	−0.027***	−0.697***
	(0.005)	(0.024)	(0.006)	(0.025)
Year FE	Yes	Yes	Yes	Yes
Drug FE	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes
Chain FE	Yes	Yes	Yes	Yes
Pharmacy FE	No	No	No	No
Observations	850,735	1,031,572	850,735	1,031,572
R^2	0.958	0.763	0.958	0.763
Adjusted R^2	0.958	0.763	0.958	0.763
Residual Std. Error	0.177 (df = 850606)	0.602 (df = 1031441)	0.177 (df = 850606)	0.602 (df = 1031441)
F Statistic	149,886.700*** (df = 128; 850606)	25,582.470*** (df = 130; 1031441)	149,884.200*** (df = 128; 850606)	25,580.640*** (df = 130; 1031441)

*p<0.1; **p<0.05; ***p<0.01

effect and it is always positive. The more manufacturers of a drug a pharmacy sells the more surplus it can extract from the insurers. This is likely because a pharmacy can more easily substitute the drug. The number of insurers that cover a drug has a very small effect for branded drugs but a larger effect for generics. For generics, this effect is always positive. In other words, the more insurers that cover a drug, the more the insurers reimburse the pharmacies. This is as expected since more insurer competition should lower their individual bargaining power. Interestingly, the number of enrollees has virtually no effect for either branded or generic drugs, indicating that insurer size is not an important aspect of negotiated prices. Last, the pharmacy competition measures have very small effects for branded drugs, but larger effects for generics and these effects are positive, meaning the more pharmacy competitors the higher the negotiated price. This seems counterintuitive, but perhaps pharmacies in more populated urban locations are able to command higher prices from insurers. This result is also consistent with previous work that has found higher physician prices in more concentrated markets Dunn (2012).

In summation, for branded drugs list price seems to be the only important factor for determining negotiated prices. This is because there is little left over available surplus for the pharmacy and insurer to bargain over as almost all available surplus is accruing to the manufacturer. For generic drugs, list price is still important but much less so. Various competition measures such as the number of manufacturers, number of insurers, and number of pharmacies play a role for determining the negotiated prices of generic drugs.

3.3 Conclusion

Differential bargaining power among pharmacies and insurers can result in large amounts of price variation in the negotiated prices across pharmacies, particularly

for generic medications. Determining how these different prices are formed can be an important step in understanding how bargaining and competition among pharmacies and insurers can affect health care costs. Given recent policy debates regarding the use of PBMs and manufacturer discounts, understanding the mechanics behind negotiated prices are of utmost importance.

Additionally, understanding how insured patients' out of pocket prices are formed can help measure the gain or loss of patient welfare when becoming insured or when switching insurance companies. Though many papers have examined the effects of the cash price on uninsured patients, very few have examined the effects for patients with prescription insurance coverage, which make up almost 92% of Americans.

There are two potential directions for future work. First is to continue using negotiated prices and measure bargaining outcomes between pharmacies and insurers similar to our previous work in Linde et al. (2019). As in that paper we can construct a structural bargaining model to measure the impact of various bargaining determinants on bargaining power. This has the advantage of leveraging previous work as well as expanding on that paper to include US data.

A second option is to concentrate more on out of pocket prices and patient welfare. This is perhaps more interesting and impactful but requires much more additional work including obtaining pharmacy data for Medicare and Medicaid to establish benchmark patient prices. We are currently investigating the feasibility of obtaining such data.

Appendix

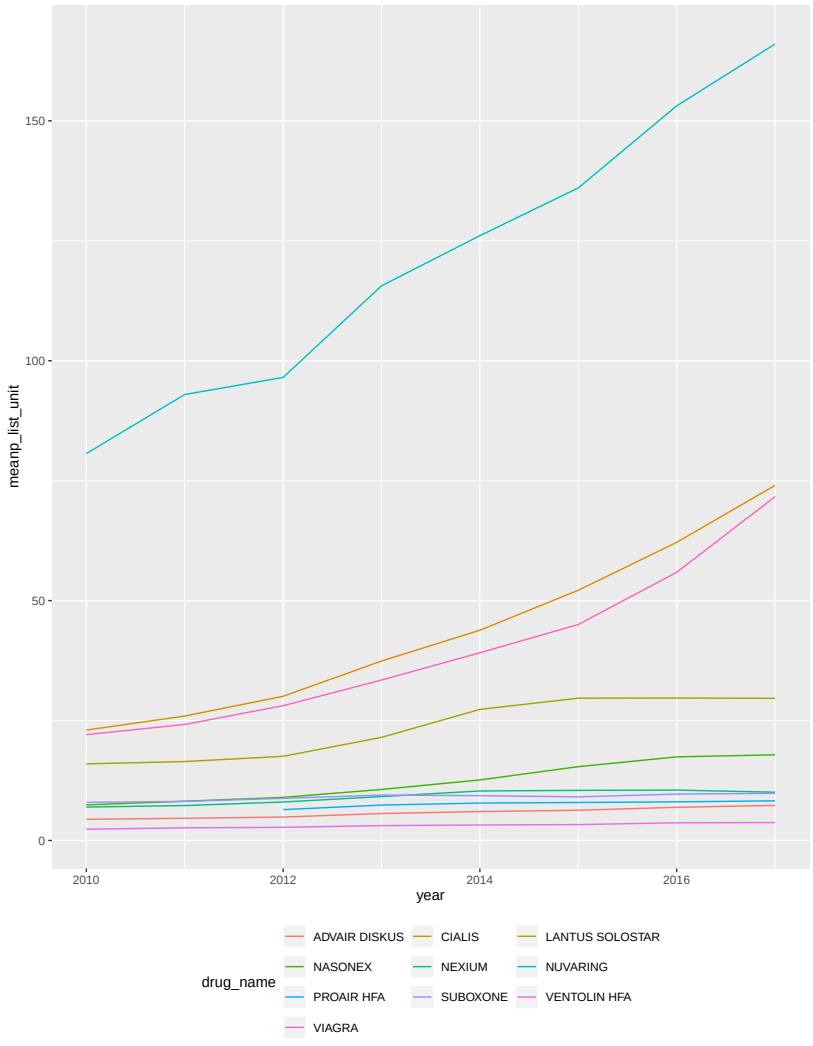

Figure 3.11. Prices over Time: List Prices for Sample of Branded Drugs

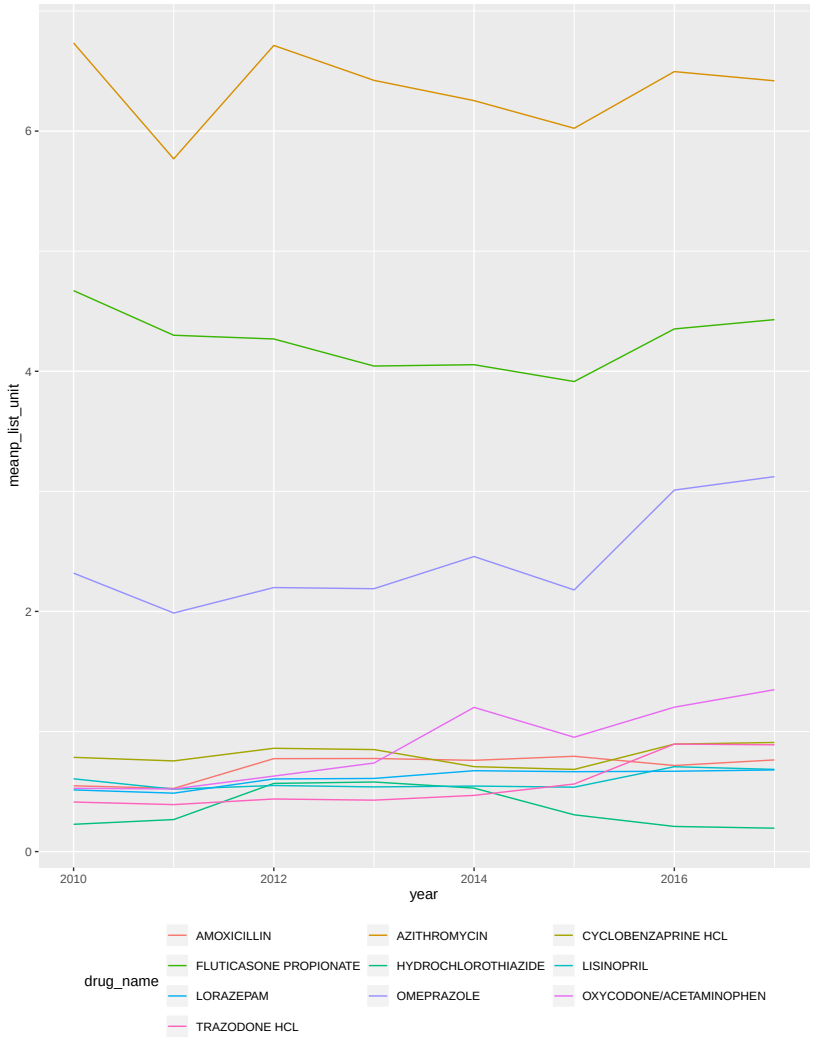

Figure 3.12. Prices over Time: List Prices for Sample of Generic Drugs

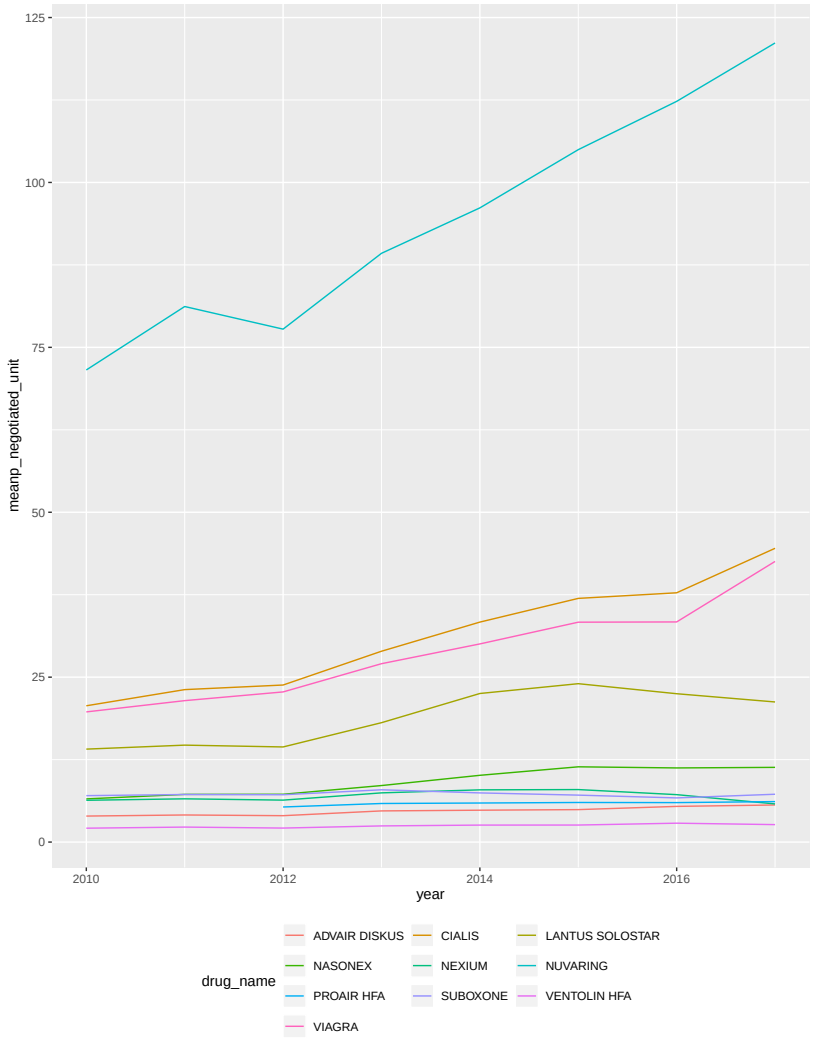

Figure 3.13. Prices over Time: Negotiated Prices for Sample of Branded Drugs

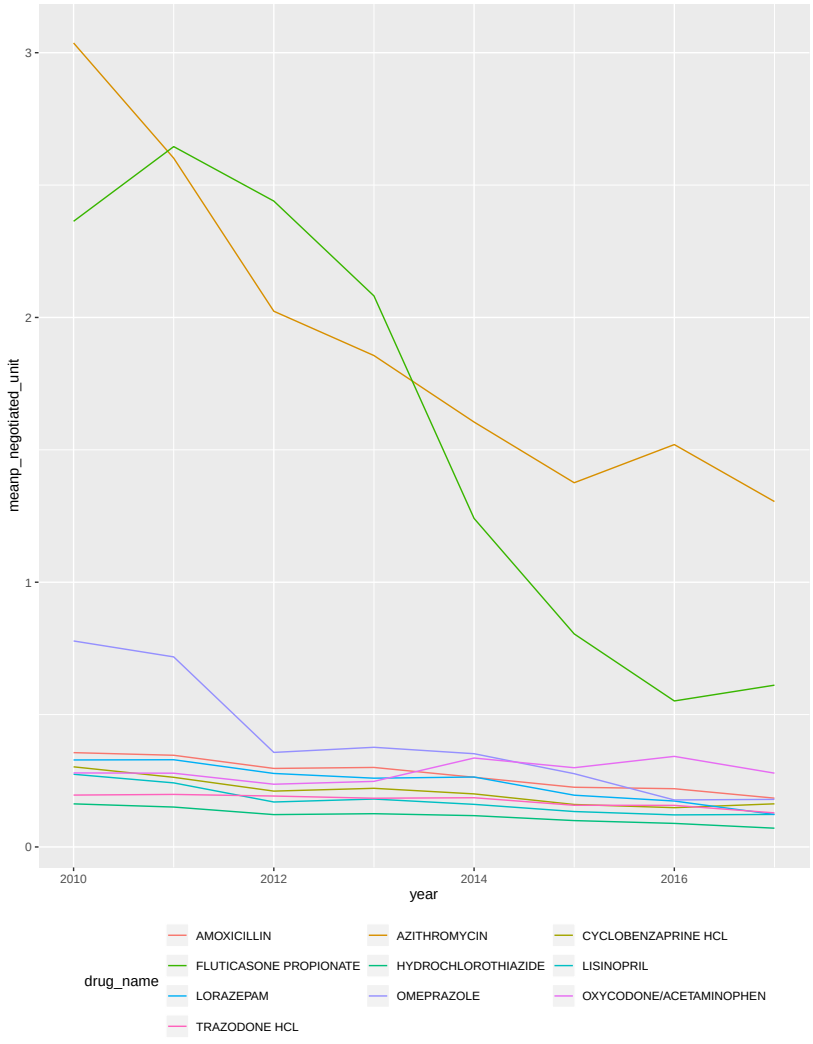

Figure 3.14. Prices over Time: Negotiated Prices for Sample of Generic Drugs

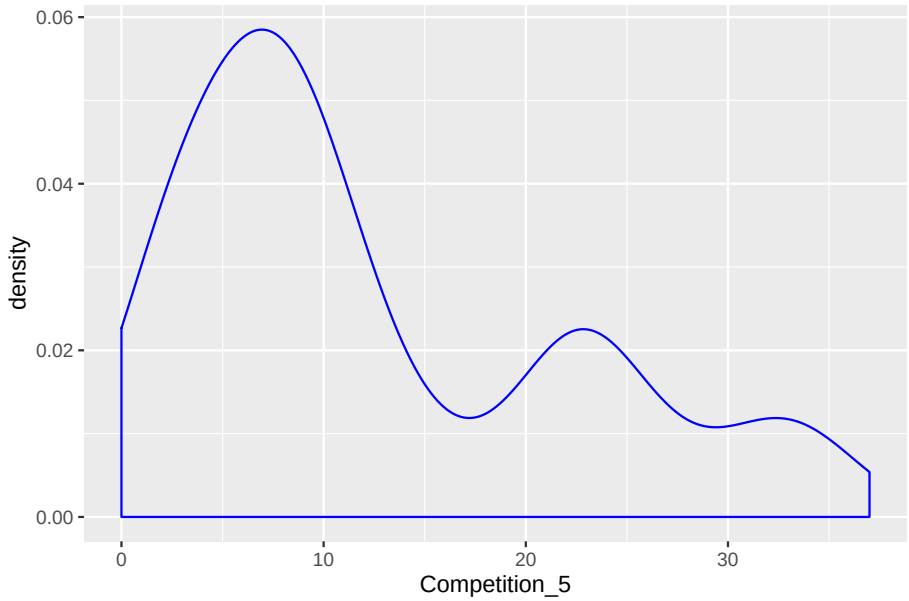

Figure 3.15. Density of Retail Pharmacy Competition - Five Miles

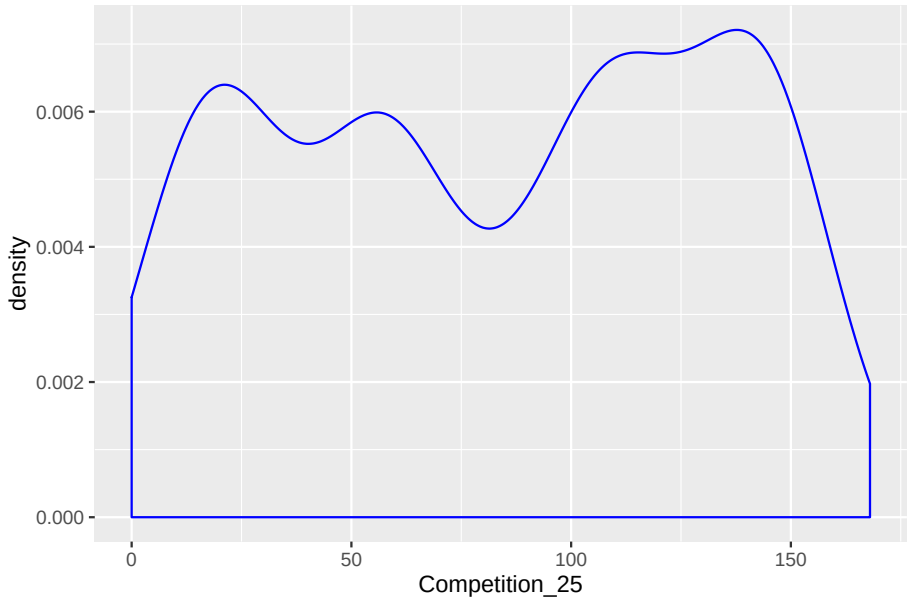

Figure 3.16. Density of Retail Pharmacy Competition - Twenty-five Miles

4. ACCOUNTABLE CARE ORGANIZATIONS AND PHYSICIAN ANTIBIOTIC PRESCRIBING BEHAVIOR

Many antibiotics prescriptions written by physicians in inpatient and outpatient settings are considered unnecessary (Griljalva et al. (2009)). CDC studies estimate that about 30% of all antibiotic prescriptions in the US doctors' offices and emergency departments are written for infections that don't require antibiotic treatment.[1] These studies also suggest that even when antibiotics are required for infection treatment, the treatment courses are often longer than recommended (CDC (2019)). Such inappropriate antibiotic prescribing can lead to serious adverse side effects in patients and contribute to antibiotic resistance, which is both a growing public health threat and increases health care costs (Spellberg et al. (2008)). The current literature primarily focuses on the effectiveness of hospital antimicrobial utilization improvement programs using data on individual facilities, specific settings, or specific conditions (Abuali et al. (2019); Andrajati et al. (2017); Ashworth et al. (2005); Barlam et al. (2015); Butler et al. (2012)). However, little is known about the general driving factors behind physician-level antibiotic prescribing as well as potential peer effects. In this paper we quantify the causal spillover effect of joining an Accountable Care Organization (ACO) on antibiotic prescribing behavior.

ACOs are groups of health care providers that coordinate care for Medicare patients with the goal of achieving a higher standard of care as well as reduced costs of care. ACOs were designed to align the incentives of health providers with the goals of the overall Medicare system by exposing health providers to the costs of care. If

[1]Antibiotics only treat certain infections caused by bacteria, and do not work on viruses that cause colds, flu, and most cases of bronchitis. Antibiotics are usually not needed for common bacterial infections (https://www.cdc.gov/antibiotic-use/community/about/can-do.html).

ACOs achieve high levels of care and cost savings they capture a percentage of that savings as profit. However, some types of ACOs may face downside risk if they fail to achieve sufficient outcome scores.[2] Previous work suggests that ACOs have had some modest success in improving care and reducing spending (McWilliams et al. (2015), Kaufman et al. (2019)). ACO membership could influence antibiotic prescribing in several ways. Since patient satisfaction scores are an explicit outcome for determining ACO effectiveness, a physician might increase prescribing after joining an ACO in order to improve patient satisfaction metrics. On the other hand, a desire to reduce costs might result in fewer prescriptions. There is little theoretical reason to expect either effect to dominate.

Naturally, a number of individual and institutional features may influence physicians antibiotic prescribing behavior, which we measure by the total number of antibiotic prescriptions written for Medicare Part D patients. Many of these features are observable. We divide these observable features in to four categories: physician characteristics, physician affiliations, patient characteristics, and volume.

There may also be unknown or unobserved characteristics that explain antibiotic prescription behavior such as the physician's own expectation of future resistance risk, their discount rate of that future risk, the patient's beliefs about their condition, the patient's insistence on receiving a prescription, etc. All of these can be contributors to a physician's likelihood of prescribing an antibiotic but cannot be observed.

In this paper we focus on identifying the spillover effects that physician ACO participation has on their antibiotic prescribing behavior. The identification of this effect is complicated by the treatment (ACO participation) not being randomly assigned to physicians, and as such, this presents a selection problem due to the choice to either receive the treatment or not. This decision about whether or not to become affiliated

[2]See https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/for-acos/index for more information.

with an ACO may be driven by both the observable characteristics mentioned above (which we are able to adjust for) as well as by characteristics that are not observed by the econometrician but which may simultaneously affect antibiotic prescribing. In order to address these empirical challenges we employ a two-part structural model that accounts for both the decision to join an ACO and the effect that this has on the physician's subsequent antibiotic prescribing behavior.

To analyze this model we use three datasets: Medicare Part D claims, Medicare Part B claims, and Physician Compare.[3] These data allow us to control for many variables relating to patients and physicians.

We find that ACO affiliation helps reduce antibiotic prescribing by 23.9 prescriptions (about 23%) per year. The treatment effect is found to vary with specialty. Internal medicine physicians experience an average decrease of 19%, family and general practice physicians a decrease of 16%, and nurse practitioners a decrease of 12.5% in their antibiotic prescribing per year. In terms of selection into treatment, we show that failure to account for selection on physician unobservable characteristics results in an understating of the average treatment effects.

We contribute to a number of existing literatures. First, we contribute to the literature on antibiotic prescribing behavior and the impact of antibiotic resistance by showing one channel in which antibiotic prescribing could be reduced. Second, we contribute to the literature on the effectiveness of Accountable Care Organizations by showing a previously unknown, and beneficial, spillover effect of ACOs.

4.1 Model

To explain antibiotic prescribing behavior and isolate the effect of ACO membership we use a directed acyclical graphical model. Figure 4.1 illustrates how observed

[3]See section 3 for more details.

and unobserved characteristics affect both membership in ACOs and antibiotic prescriptions. Our primary outcome of interest, *AB Claims*, is the total number of antibiotic prescriptions a physician writes for Part D patients. In this paper we do not differentiate between types of antibiotics, or attempt to determine if the prescription was inappropriate, as our goal is only to identify the causal effect of ACO participation on the overall volume of prescriptions. However, any reduction in antibiotic utilization as a result of ACO participation is likely to include a decrease in unnecessary prescribing given the sheer proportion of antibiotic overuse estimated by the literature. Furthermore, ACOs incentivize doctors to reduce unnecessary care while maintaining high healthcare quality standards.

A physician is part of the treatment group if he or she is a member of an ACO at any point during a given year. Initially it is unclear what effect membership in an ACO will have on antibiotic prescribing behavior. There is little previous work on the influence of peers or group affiliations on antibiotic prescribing behavior. One exception is Charani et al. (2013), which found an existence of an "etiquette" on antibiotic prescribing within a practice group but that many physicians felt they had the autonomy to prescribe as they wished. However, the paper is limited to surveys of a small sample of physicians in only four hospitals and is not specific to ACOs. Additionally, their results do not predict the direction of the effect that being in a group practice would have on prescribing behavior. It is plausible that, if physicians care about future antibiotic resistance, there would be social pressure on ACO members to limit prescribing. Additionally, social pressure to reduce overall costs could limit unnecessary prescribing. However, there is a trade off between prescribing behavior and patient satisfaction if patients generally expect to receive a prescription when visiting the doctor (Ashworth et al. (2016)). If patient satisfaction scores are more important to ACO members than antibiotic resistance then it is also

plausible that ACO membership could increase antibiotic prescribing. Thus, both the direction and magnitude of the treatment effect is ultimately an empirical question.

The top row in Figure 4.1 shows four categories of observable characteristics. The dashed black lines indicate that these observable characteristics are associated with both antibiotic prescribing and membership in ACOs. First, the volume of patients a physician sees will clearly influence the number of prescriptions he or she writes. Volume might also make a physician more attractive to an ACO since there is a higher potential for efficiency savings (and, thus, opportunity for profit) with more patients.

Second, we consider patient characteristics such as age, sex, income, etc. These will be described in detail in the next section. Some studies have found that patient race, sex, and concurrent conditions affect antibiotic prescribing (Gerber et al. (2013); Sun et al. (2006)). Other studies have found the opposite, that many of these pa-

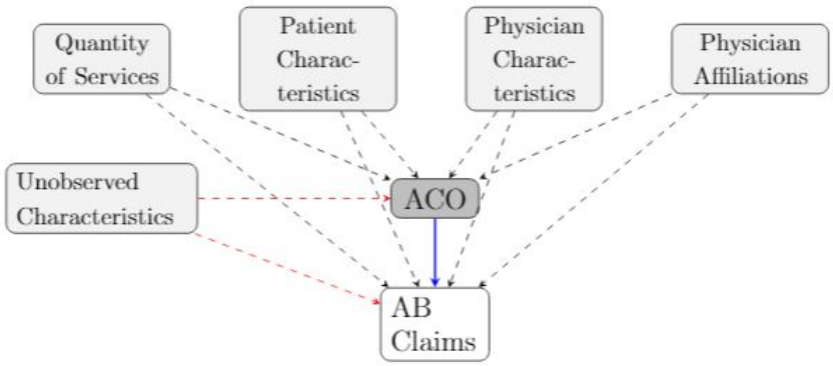

Figure 4.1. Causal Directed Acyclical Graph Diagram

Figure 4.1 shows a DAG model of antibiotic prescribing. Categories of observable variables, as well as unobserved characteristics, have a causal effect on both ACO membership and antibiotic prescribing. ACO membership itself also has a causal effect on antibiotic prescribing.

tient characteristics do not influence antibiotic utilization by doctors (Steinman et al. (2006)).

Certain observable physician characteristics are also likely to have effects on prescription behavior and ACO membership. These include primary specialization, physician sex, strength of the medical school the physician attended, and use of electronic health records. Previous work has shown that physician specialty and sex can affect antibiotic prescribing (Steinman et al. (2006); Sun et al. (2006); Wang et al. (2009)). The physical location of the physician's office also matters (Steinman et al. (2006); Sun et al. (2006); Wang et al. (2009)). We control for the type of commuting area the provider is located in (urban or rural), as well as their hospital referral region.

Last, to help ensure we isolate the effect of ACO participation rather than the general attitude of the physician to collaboration and group practice, we account for several group practice and affiliation variables. These include the number of practices the physician belongs to, the number of hospital affiliations, and the total number of members in the physician's practices. Although no papers have specifically examined the relationship between ACO membership and antibiotic prescribing, several have looked at some aspect of group practice. Parente et al. (2017) found a difference between prescribing in teaching versus non-teaching hospitals. Steinman et al. (2006) found an effect for membership in a Health Maintenance Organization (HMO). Charani et al. (2013) explains prescribing etiquette for a small sample of hospitals but makes no quantitative prediction of the effect on antibiotic prescribing.

Even with many observed variables, simply controlling for them and running a multivariate regression of ACO membership on antibiotic prescribing is problematic because ACO membership is not randomly assigned. Physicians self-select into ACO membership and there are at least some potential unobserved characteristics that

could be correlated with both ACO membership and antibiotic prescribing.[4] We show this graphically in Figure 4.1 by the red dashed lines. This endogeneity problem means Ordinary Least Squares coefficient estimates will be biased. We describe how we test for and solve this problem using a two-part structural selection model in the Statistical Analysis section. Once we account for this issue we can measure the actual treatment effect of ACO membership, represented by the solid blue line in Figure 4.1.

4.2 Methods

4.2.1 Study Population and Data Sources

We analyze Medicare Part D antibiotic claims for a panel of providers for years 2016 and 2017. Three data sources are utilized - Medicare Part D, Medicare Part B (also referred to as Physician and Other Supplier), and Physician Compare datasets.

The antibiotic claims and other prescription data come from Part D Prescriber Public Use File (PUF). The primary data source for the Part D PUF is the Centers for Medicare & Medicaid (CMS) Chronic Conditions Data Warehouse, which contains Medicare Part D prescription drug events (PDEs) of Medicare beneficiaries with a Part D prescription drug plan. The data contains information on drug utilization and costs for beneficiaries enrolled in the Medicare Part D prescription drug program.[5] Provider demographics is based on information extracted from National Plan Provider Enumeration System (NPPES).

The Physician and Other Supplier PUF contains final-action claims information on Medicare Part B services and procedures provided to Medicare beneficiaries enrolled

[4]For example, the extent to which a physician values patient satisfaction could influence their willingness to provide an unnecessary antibiotic as well as how attractive they would be as a potential ACO member.

[5]This makes up about 70% of all Medicare beneficiaries, of which about two-thirds are enrolled in stand-alone Prescription Drug Plans and one-third enrolled in Medicare Advantage Prescription Drug Plans.

in the fee-for-services program. Part B covers physician office visits, lab and diagnostic tests, medical equipment, ambulance, and other outpatient services.

Created by CMS in Dec 2010 as a requirement of the Affordable Care Act (ACA) of 2010, the Physician Compare dataset contains up-to-date information on physicians and groups enrolled in Medicare, including performance and quality measures. It was created to help patients make informed choices about their medical care. It contains data on innovative model participation (ACOs), Electronic Health Record Technology participation, performance information, and patient survey scores.

Our data sources identify the providers by their National Provider Identifier (NPI). We use physician NPI and year to match physicians in the three datasets. After dropping non-US based physicians, the final sample for 2016-2017 consists of 1,120,690 observations (a total of 645,620 physicians, most of which are in both years of the data). About one third of the physicians belonged to an ACO in this time frame. Since the majority of non-pediatric primary care doctors (93%) accept Medicare,[6] our sample captures most physicians practicing in the US (Boccuti et al. (2015)).

4.2.2 Study Variables

ANTIBIOTIC PRESCRIBING AND ACCOUNTABLE CARE ORGANIZATIONS

We use Medicare Part D yearly antibiotic claims for each physician as a measure of antibiotic prescribing. Since older adults utilize about 50% more antibiotics per person than younger adults and have the highest risk for antibiotic-related adverse outcomes, this population is particularly important to examine (Olesen et al. (2018)).

[6]This number is comparable to the proportion of physicians that accept private insurance, which is 94%.

Because physician-level claims are suppressed if they fall in the interval 1-10, we impute the mean value and conduct a robustness test that accounts for censoring.[7]

The main explanatory variable of interest is the physicianâs ACO participation. We utilize an indicator variable that is equal to one if the provider belongs to an ACO in a given year. Our ACO measure comes from the Physician Compare dataset and accounts for participation in any of the ACO programs offered by Medicare, including Medicare Shared Savings Program, ACO Investment Model, Advance Payment ACO Model, Comprehensive ESRD Care Initiative, Next Generation ACO Model, Pioneer ACO Model, and Vermont All-Payer ACO Model.[8]

PROVIDER CHARACTERISTICS AND AFFILIATIONS

In order to account for group- and peer-level factors that affect prescribing behavior and probability of selection into ACOs, we include as controls the number of practices that the physician is a part of, the total number of group members across those groups, as well as the number of hospitals that the physician is affiliated with.

Because doctors who utilize electronic health records (EHRs) are potentially more aware of patientsâ overall healthcare utilization patterns and prescription history, as well as have better access to diagnostic test results, such physicians may also prescribe antibiotics differently compared to those who do not use EHRs. Furthermore, ACO participation incentivizes coordination to deliver quality care to patients, which requires extensive use of technology such as referral systems and EHRs. We include a dummy variable for whether the physician uses EHRs to account for technological proficiency. Because attending a top medical school is a proxy for a physicianâs

[7]See Appendix B.

[8]For more information on various ACO models, see https://innovation.cms.gov/innovation-models/aco.

training quality, it may play a role in prescribing habits and coordination ability. An indicator variable for whether the physician attended a top 25 medical school is included in the model to control for medical education quality.[9] An indicator variable for whether the doctor is a female accounts for any gender differences in prescribing patterns and coordination skills. Finally, physician specialty fixed effects control for differences in antibiotic prescribing across practice types, as well as variation in how specialties deal with preventative care, coordination, and underlying services, which may also affect the probability of joining an ACO.

PATIENT CHARACTERISTICS AND OTHER COVARIATES

Since the underlying patient population's health and socioeconomic status may play an important role in the providerâs prescribing patterns and the decision to join an ACO, our model includes the physicianâs part B beneficiariesâ average age and average risk score.[10]

Previous literature suggests that time- and patient-pressure may be an important determinant in how physicians prescribe antibiotics. Some reasons for unnecessary antibiotic prescriptions include pressure to meet patientsâ expectations, fear of complications, and fatigue (Feller (2019)). Because these factors are likely to increase with the volume of patients and may affect the providerâs decision to join an ACO, we include as covariates the total number and charges for Part B physician services, as well

[9]Our ranking is based on the U.S. News annual rankings of medical schools across research and primary care.

[10]CMS developed a risk-adjustment model that uses HCCs (Hierarchical Condition Categories) to assign risk scores. Risk scores are based on a beneficiaryâs age and sex; whether the beneficiary is eligible for Medicaid, first qualified for Medicare on the basis of disability, or lives in an institution; and the beneficiaryâs diagnoses from the previous year. The scores estimate how beneficiariesâ fee-for-services spending will compare to the overall average for the entire Medicare population. Beneficiaries with scores greater than the average risk score are expected to have above-average spending, and vice versa.

as the number of patients receiving them. The physicianâs prescribing preferences are captured by the number and the cost of part D claims.

To account for geographic and population density factors that may affect both ACO participation and prescribing practices, our model includes the Hospital Referral Region (HRR) and Rural-Urban Commuting Area (RUCA) fixed effects. HRRs are 306 geographical units for tertiary care for Medicare beneficiaries. Each HRR is required to have a minimum population of 120,000, have the largest proportion of major cardiovascular procedures, and the residents of each HRR must receive at least 65% of their hospitalizations within that HRR.[11] The RUCA codes classify U.S. census tracts using population density, urbanization, and commuting.[12] We utilize 10 primary whole-number codes that delineate metropolitan, micropolitan, small town, and rural commuting areas.[13]

4.2.3 Data Descriptives

Table 4.1 presents summary statistics for the full sample of physicians separated into ACO and non-ACO categories.[14] In the full sample of physicians, about one-third belong to an ACO. ACO affiliated doctors tend to have fewer antibiotic claims. They have more affiliations, are more likely to graduate from a top medical school, more likely to use electronic health records, and are more likely to be a female. Additionally, both the patient populations as well as the services-related characteristics of ACO and non-ACO affiliated doctors are significantly different. Such differences highlight

[11]See https://www.dartmouthatlas.org for more details on HRR.
[12]See https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes.aspx for details on RUCA codes.
[13]The secondary non-whole number codes, which represent further subdivisions, were rounded to the nearest whole number for simplicity.
[14]Additional summary statistics for the full sample of providers, as well as the sample of physicians who prescribed antibiotics, can be found in Appendix A Table 4.5.

the importance of controlling for the observable characteristics when estimating the effect of ACO participation on prescribing behavior.

Table 4.2 contains summary statistics for three select specialties - internal medicine, family and general practice, and nurse practitioners. Together these specialties ac-

Table 4.1.
Summary Statistics by ACO Participation

	ACO=1		ACO=0		
Variable	**Mean**	**SD**	**Mean**	**SD**	**Diff.**
Outcome Variable					
Antibiotic Claims	71.88	119.11	72.70	133.52	0.82***
Physician Affiliations					
Number of Practices	1.27	0.58	1.11	0.52	-0.16***
Number of Hospital Affiliations	2.18	1.44	1.85	1.51	-0.34***
Number of Practice Members	631.85	747.04	262.86	647.86	-368.99***
Physician Characteristics					
Top Medical School Indicator	0.14	0.35	0.13	0.33	-0.02***
Uses Electronic Health Records	0.44	0.50	0.32	0.47	-0.12***
Experience	19.36	12.03	21.56	12.88	2.20***
Female Physician Indicator	0.43	0.50	0.38	0.48	-0.06***
Patient Characteristics					
Average Age of Part B Ben.	71.19	4.98	71.13	5.52	-0.06***
Average Risk Score of Part B Ben.	1.69	0.76	1.63	0.81	-0.06***
Number of Female Part B Ben.	206.19	249.63	211.39	240.17	5.21***
Low-Income Sub. Part D Claims	823.72	2,002.81	951.61	2,673.48	127.89***
Low-Income Sub. Replace Ind.	0.06	0.23	0.08	0.27	0.02***
Quantity of Services					
Number of Part D Claims	2,229.57	3,741.34	2,109.91	4,028.09	-119.67***
Cost of Part D Claims	231,228.30	441,038.90	222,856.10	460,859.20	-8,372.17***
Total Part B Services	2,568.95	12,111.98	3,550.19	18,896.36	981.24***
Total Charges for Part B Services	338,203.10	671,071.90	417,216.80	968,628.40	79,013.64***
Part B Ben. Receiving Services	368.32	457.25	371.96	428.93	3.65***
N	300,023		820,667		

Total Observations = 1,120,690
Total Physicians = 645,620

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

count for 67.2% of all antibiotic claims. About one-third of providers in each specialty category are affiliated with an ACO, and, with the exception of nurse practitioners, tend to prescribe more antibiotics compared to the average physician in the full sample.

Table 4.2.
Summary Statistics for Select Specialties

	Internal Medicine	**Family & General Practitioners**	**Nurse Practitioners**
All Physicians			
% of Total Antibiotic Claims	27.2	29.1	10.9
% of Specialty in ACO	32.4	31.0	29.4
Mean Antibiotic Claims	131.51	154.28	61.70
N	167,792	152,969	143,384
Antibiotic Prescribers			
% of Total Antibiotic Claims	27.2	29.1	10.9
% of Specialty in ACO	31.9	31.1	30.1
Mean Antibiotic Claims	143.44	160.46	84.43
N	153,836	147,082	104,787

4.2.4 Statistical Analysis

In order to estimate the spillover effects that ACO affiliation has on physicians' antibiotic prescribing behavior we employ a potential outcomes framework, a la Rosenbaum and Rubin (1983). Let $AB_{it}(ACO_{it})$E denote the antibiotic prescribing by physician i, in period t, where $ACO_{it} \in \{0, 1\}$ is an indicator for whether physician i is affiliated with an ACO, then the sought average treatment effect is given by

$$\tau = E\left[AB_{it}(1) - AB_{it}(0)\right],$$

where $AB_{it}(1)$ denotes the antibiotic prescribing of physician i if they are treated ($ACO_{it} = 1$), and $AB_{it}(0)$ denotes the counterfactual outcome for physician i if they are untreated ($ACO_{it} = 0$). A problem confronting the estimation of the average treatment effect (τ) in our setting is that physicians self-select into treatment, that is, we do not have random assignment of our treatment (ACO affiliation). To address this we draw on our behavior model (from Section 2) to help inform our set of control variables, x_{it}, which account for: (i) physician characteristics, (ii) physician affiliations, (iii) physician quantity of services, and (iv) patient characteristics. However, as also noted within our behavioral model, physicians may self-select into treatment based on unobservable characteristics that can also influence their antibiotic prescribing behavior, causing our treatment to be endogenous.

In order to resolve this endogeneity concern we use a two-part structural selection model that allows us to control for selection into treatment based on both observable and unobservable physician characteristics. Here, our outcome regression of interest is given by,

$$AB_{it} = \alpha + x_{it}\beta + \tau ACO_{it} + \varphi_t + \lambda_s + \nu_h + \kappa_r + \epsilon_{it}, \tag{4.1}$$

where our observed treatment (ACO_{it}) depends on the latent utility U^*_{it} that physician i gets from selecting into treatment, that is,

$$ACO_{it} = \begin{cases} 1 & \text{if } U^*_{it} = \delta + w_{it}\gamma + \eta_t + \psi_s + \chi_h + \upsilon_r + u_{it} > 0 \\ 0 & \text{if } U^*_{it} = \delta + w_{it}\gamma + \eta_t + \psi_s + \chi_h + \upsilon_r + u_{it} \leq 0 \end{cases}. \tag{4.2}$$

In Equations (4.1) and (4.2) φ_t and η_t denote time fixed effects, λ_s and ψ_s capture specialty fixed effects, ν_h and χ_h control for geographic variation across hospital referral regions, κ_r and υ_r are fixed effects for how urban/rural a given area is, and

the residuals ϵ_{it} and u_{it} are bivariate normal with mean zero and a covariance matrix structure given by:

$$\begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix}.$$

We estimate this structural model using the Heckman (1976, 1978) two-step procedure as outlined by Maddala (1986). In the first step we obtain probit estimates for the parameters $(\hat{\delta}, \hat{\gamma}, \hat{\eta}_t, \hat{\psi}_s, \hat{\chi}_h, \hat{\upsilon}_r)$ from Equation (4.2), using an exclusion restriction for experience such that $w_i = [x_{it}, experience_{it}]$.[15] Using these estimates we compute the hazard rate, h_{it}, for each observation as

$$h_{it} = \begin{cases} \phi(\hat{\delta} + w_{it}\hat{\gamma} + \hat{\eta}_t + \hat{\psi}_s + \hat{\chi}_h + \hat{\upsilon}_r)/\Phi(\hat{\delta} + w_{it}\hat{\gamma} + \hat{\eta}_t + \hat{\psi}_s + \hat{\chi}_h + \hat{\upsilon}_r) & \text{if } ACO_{it} = 1 \\ -\phi(\hat{\delta} + w_{it}\hat{\gamma} + \hat{\eta}_t + \hat{\psi}_s + \hat{\chi}_h + \hat{\upsilon}_r)/\left(1 - \Phi(\hat{\delta} + w_{it}\hat{\gamma} + \hat{\eta}_t + \hat{\psi}_s + \hat{\chi}_h + \hat{\upsilon}_r)\right) & \text{if } ACO_{it} = 0 \end{cases},$$

and, using the hazard rate, we estimate the revised outcome equation,

$$AB_{it} = \alpha + x_{it}\beta + \tau ACO_{it} + \rho\sigma h_{it} + \varphi_t + \lambda_s + \nu_h + \kappa_r + \epsilon_{it}, \tag{4.3}$$

within the second and final step. As noted, the important benefit of this approach is that it allows us to control for potential selection on unobservables in order to resolve our treatment endogeneity concern.[16]

As such, our identification strategy for obtaining our estimates rests on the conditional independence assumption that treatment is assigned as good as random once we control for selection on observables, x_{it}, the unobservables (captured by the hazard

[15] Previous work has found that physician experience is uncorrelated with antibiotic prescribing (Barlam et al. (2015)). Moreover, Donohue et al. (2018) impose similar exclusion restrictions pertaining to physician age within their study of physician drug adoption.

[16] Another benefit of this approach is that it allows us to directly test for treatment endogeneity within our final regression, Equation (4.3), by seeing if the estimate $\hat{\rho\sigma}$ is significant.

h_{it}), potential time effects, φ_t, specialty effects,λ_s, hospital referral region effects, ν_h and how rural the region is, κ_r. Stated formally, our identification rests on:

$$\{AB(0), AB(1)\} \perp ACO_{it} \mid x_{it}, h_{it}, \varphi_t, \lambda_s, \nu_h, \kappa_r.$$

4.3 Results

4.3.1 Ordinary Least Squares Regression Results

Table (4.3) displays the coefficient estimates obtained by Ordinary Least Squares (OLS) regression. Columns 1 and 2 present the estimated effects of ACO participation on antibiotic claims for the full sample of physicians, and columns 3 and 4 effects are estimated for the physicians who had more than zero antibiotic claims for years 2016 and 2017.

Column 1 results indicate that physicians who participate in ACOs have on average 2.6 fewer yearly antibiotic claims than non-ACO providers[17], which represents a 3.5% decrease from the average antibiotic prescribing for the full sample. However, because antibiotic prescribing is likely to vary by specialty, we expect the effect of ACO to be heterogeneous across different types of practices. In column 2 we include interacted specialty by ACO dummy variables for specialties with the highest proportion of antibiotic prescribing - internal medicine physicians, doctors who are in general/family practice, and nurse practitioners. Together, these specialties account for 67.2% of all antibiotic claims. The estimates suggest the presence of heterogeneity in how ACO participation affects prescribing across provider types, with all ACO-related coefficients being significant at 1% significance level. Internal medicine physicians who are part of an ACO have 13.2 fewer antibiotic claims relative to their

[17]Significant at 1% level.

Table 4.3.
Effect on Antibiotic Claims (2016-2017) - Ordinary Least Squares (OLS)

	All (1)	All (2)	Prescribers (3)	Prescribers (4)
ACO Participation				
ACO Participation	-2.556***	1.281***	-4.788***	-0.623
	(0.222)	(0.266)	(0.292)	(0.416)
ACO x Internal Medicine		-14.53***		-12.07***
		(0.620)		(0.733)
ACO x Family & General Practice		-12.37***		-10.56***
		(0.678)		(0.761)
ACO x Nurse Practitioner		4.394***		4.678***
		(0.559)		(0.712)
Physician Affiliations				
Number of Practices	0.668***	0.732***	0.704**	0.780***
	(0.196)	(0.196)	(0.290)	(0.290)
Number of Hospital Affiliations	1.112***	1.089***	1.545***	1.530***
	(0.107)	(0.107)	(0.169)	(0.169)
Number of Practice Members	-0.000**	-0.000***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Physician Characteristics				
Top Medical School Indicator	-2.740***	-2.674***	-3.559***	-3.502***
	(0.314)	(0.314)	(0.441)	(0.441)
Uses Electronic Health Records	-7.030***	-6.764***	-9.295***	-8.981***
	(0.266)	(0.265)	(0.376)	(0.376)
Female Physician Indicator	-4.663***	-4.579***	-6.397***	-6.290***
	(0.252)	(0.251)	(0.387)	(0.386)
Patient Characteristics				
Average Age of Part B Ben.	1.345***	1.334***	1.080***	1.078***
	(0.0307)	(0.0306)	(0.0597)	(0.0596)
Average Risk Score of Part B Ben.	-4.106***	-4.118***	-4.485***	-4.481***
	(0.178)	(0.177)	(0.254)	(0.254)
Number of Female Part B Ben.	-0.0491***	-0.0484***	-0.0590***	-0.0588***
	(0.007)	(0.007)	(0.010)	(0.010)
Low-Income Sub. Part D Claims	-0.003***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
Low-Income Sub. Replace Ind.	-15.770***	-15.630***	-25.520***	-25.190***
	(0.192)	(0.192)	(0.433)	(0.432)
Quantity of Services				
Number of Part D Claims	0.025***	0.025***	0.024***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
Cost of Part D Claims	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Part B Services	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Charges for Part B Services	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Part B Ben. Receiving Services	0.043***	0.043***	0.068***	0.068***
	(0.004)	(0.004)	(0.006)	(0.006)
Observations	1,120,690	1,120,690	777,172	777,172
Specialty FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R^2	0.629	0.630	0.620	0.620

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

non-ACO counterparts.[18] Given that internal medicine providers write 131.51 antibiotic prescriptions on average, the estimated effect for this specialty corresponds to about a 10% decline in claims from ACO membership. Family and general practice physicians have 11.1 fewer antibiotic claims compared to the same type of doctors who are not participating in ACOs - a 7% decrease from the average for that specialty. The ACO-participating nurse practitioners, on the other hand, appear to have 5.7 more antibiotic claims than non-ACO ones, which is about a 9% increase from the mean. The ACO coefficient is positive and significant, indicating that providers in specialties other than ones accounted for by the interaction terms may experience an increase in antibiotic prescribing of about 1.3 claims due to ACO participation.

The ACO coefficient estimate in column 3 indicates that the effect of ACO participation on antibiotic claims may be greater for the sample of physicians who prescribed antibiotics in 2016 and 2017. ACO-participating providers have 4.8 less yearly antibiotic claims than non-ACO physicians, which is significant at 1%-level and represents a 4.6% decline from the average number of claims for this sample of prescribers. When we include the specialty interaction terms in column 4, the ACO coefficient remains negative (although not significant) indicating that ACO participation may lower antibiotic prescriptions for the remaining specialties, although substantial amount of heterogeneity may be present for the remaining specialties. The results show that physicians practicing internal medicine reduce their yearly antibiotic claims by 12.1, or 8.4% of the sample mean, when they join an ACO. While family and general practitioners decrease antibiotic prescribing by 10.6 claims per year, which corresponds to 6.6% of the sample average, the nurse practitioners appear to increase their antibiotic prescribing by 4.7 claims, or 5.5% of the mean.

[18] $1.281 - 14.53 = -13.249$.

4.3.2 Structural Selection Model Estimation Results

A potential concern with these regression results is that latent features that drive physicians' ACO participation decision also influence their antibiotic prescribing behavior. For example, if a physician selects into treatment (ACO affiliation) on the basis of expected shared savings program savings, or on being less risk averse, then one might anticipate that our regression results in Table 4.3 are upward biased. To account for the potential endogeneity of ACO affiliation, Table 4.4 presents two-step regression results that control for selection on unobservables. Columns (1) and (2) present results for the full sample, while columns (3) and (4) present results for the active antibiotic prescriber subsample.

Looking at the full sample in column (1) first, we see that ACO affiliation is associated with an average 18.2 prescription reduction in antibiotic prescribing, which corresponds to about a 25% reduction. Column (2) further showcases the heterogeneity of these treatment effects. For physicians with a primary specialty in internal medicine, ACO affiliation is associated with a 24.5 antibiotic prescription (or 18.6%) reduction, while the effect for physicians with a primary specialty of family or general practice is a 22.3 prescription (or 14.5%) reduction. Looking at the treatment effect on nurse practitioners we find an overall prescribing reduction of 5.7 antibiotic prescriptions (or about a 9% reduction).

Conditioning on only prescribers gives qualitatively similar results. Firstly, as seen in column (3), the overall average treatment increases in its magnitude to a 23.9 antibiotic prescription (or about 23%) reduction. Column (4) indicates that when conditioning on prescribers, internal medicine physicians experience an average 27.2 antibiotic prescription (about 19%) reduction, while family or general practice physicians have an average 25.6 antibiotic prescription (or 16%) decrease. For nurse

Table 4.4.
Effect on Antibiotic Claims (2016-2017) - Two-Step Estimation Results.

	All (1)	All (2)	Prescribers (3)	Prescribers (4)
Accountable Care Organization Participation				
ACO Participation	-18.183***	-10.386***	-23.899***	-15.707***
	(2.033)	(1.223)	(3.082)	(3.164)
ACO × Internal Medicine		-14.069***		-11.445***
		(0.478)		(0.730)
ACO × Family & General Practice		-11.908***		-9.929***
		(0.503)		(0.768)
ACO × Nurse Practitioner		4.720***		5.186***
		(0.518)		(0.719)
Physician Affiliations				
Number of Practices	1.763***	1.537***	2.117***	1.873***
	(0.244)	(0.166)	(0.369)	(0.370)
Number of Hospital Affiliations	1.256***	1.195***	1.670***	1.625***
	(0.111)	(0.066)	(0.172)	(0.171)
Number of Practice Members	0.002***	0.001***	0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Physician Characteristics				
Top Medical School Indicator	-2.799***	-2.718***	-3.603***	-3.537***
	(0.314)	(0.234)	(0.441)	(0.441)
Uses Electronic Health Records	-5.732***	-5.812***	-7.510***	-7.606***
	(0.288)	(0.209)	(0.430)	(0.432)
Female Physician Indicator	-4.272***	-4.294***	-5.889***	-5.903***
	(0.251)	(0.185)	(0.387)	(0.387)
Patient Characteristics				
Average Age of Part B Ben.	1.378***	1.358***	1.101***	1.094***
	(0.030)	(0.018)	(0.059)	(0.059)
Average Risk Score of Part B Ben.	-4.164***	-4.159***	-4.629***	-4.590***
	(0.176)	(0.129)	(0.249)	(0.249)
Number of Female Part B Ben.	-0.050***	-0.049***	-0.059***	-0.059***
	(0.007)	(0.002)	(0.010)	(0.010)
Low-Income Sub. Part D Claims	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.000)	(0.001)	(0.001)
Low-Income Sub. Replace Ind.	-16.164***	-15.921***	-26.628***	-26.050***
	(0.198)	(0.307)	(0.458)	(0.457)
Quantity of Services				
Number of Part D Claims	0.025***	0.025***	0.024***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
Cost of Part D Claims	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Part B Services	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Charges for Part B Services	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Part B Ben. Receiving Services	0.044***	0.043***	0.068***	0.068***
	(0.004)	(0.001)	(0.006)	(0.006)
$\rho\sigma$	9.273***	6.806***	11.338***	8.745***
	(1.184)	(0.698)	(1.800)	(1.813)
Observations	1,120,690	1,120,690	777,172	777,172
Specialty FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R-squared	0.629	0.630	0.620	0.620

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

practitioners, the average treatment effect is a reduction of 10.5 prescriptions, a 12.5% fall.

Lastly, in comparing the two-step results to our naive regression results (those in Table 4.3) we see that the naive regression results indeed appear to be subject to considerable upward bias. This is further supported by the observation that our $\widehat{\rho\sigma}$ estimate is positive and statistically significant across all specifications within Table 4.4 - indicating that ACO affiliation is endogenous, and that accounting for selection on unobservables is appropriate.

4.4 Discussion

In this paper we show the effect of several observable characteristics on physician antibiotic prescribing while correcting for the endogeneity of unobserved characteristics. We confirm studies such as Gerber et al. (2013) and Sun et al. (2006) that find patient characteristics like age, sex, and concurrent conditions matter. We also show that patient income is an important aspect of antibiotic prescribing. We also confirm the many papers that show physician characteristics like specialty, geographical location, and sex matter. Beyond these, we also find that the rank of the physician's medical school and the use of electronic health records can be important determinants of antibiotic prescription behavior. Our paper is the first to quantify organizational peer effects on antibiotic prescribing behavior. We show how the number of hospital affiliations, number of practices, and number of practice members affect antibiotic prescribing. Most importantly, we are the first to show there is an effect, and quantify that effect, of ACO membership on antibiotic prescribing behavior.

As reported in the previous section, our average treatment effect shows ACO membership can reduce the number of antibiotic prescriptions by roughly a quarter. Since patient satisfaction is also an important component of measuring ACO effectiveness,

it is likely that most of the reduction in prescribing is for unnecessary antibiotics. Thus, incentivising ACO membership might provide an additional channel to reduce antibiotic resistance beyond traditional antibiotic stewardship programs. Since peer effects alone seem capable of significantly reducing antibiotic prescribing, policy makers might consider using an antibiotic stewardship component in measuring ACO performance. Rewarding low unnecessary antibiotic prescribing with additional shared savings could increase the antibiotic resistance benefit beyond what we have shown in this study.

An additional finding of our study is that average treatment effects due to ACO participation on antibiotic prescribing are heterogeneous across different medical providers and physician specialties. In particular, when conditioning on active prescribers, we observe an average 19% reduction on antibiotic prescribing for physicians with an internal medicine specialty, which is higher than that measured for physicians with a family and general practice specialty, who had an average 16% reduction, and that for nurse practitioners, who on average experience a 12.5% reduction. These differences in the relative treatment effects are particularly interesting when noting that we control for factors related to physician affiliations, physicians characteristics, patient characteristics, quantity (or volume) of services rendered, along with any systematic antibiotic prescribing behavior that may stem form the providers primary specialty, time, geography and selection into treatment. As such, this appears to be an interesting avenue for future work that may seek to further explore these heterogeneities across more specialties, and to further probe the potential sources of these heterogeneous treatment responses across specialties.

Our results present the first evidence of substantial positive spillover effects of ACO participation on antibiotic prescribing. While many papers have looked at the beneficial effects of ACO membership, their estimates may understate the societal

benefits of ACOs given that indirect effects, such as lower antibiotic prescribing, are unaccounted for. Therefore, our findings have important implications for healthcare policy. Given the increasing importance of containing the growth of antibiotic resistance, policymakers have focused on reducing unnecessary antimicrobial prescriptions primarily through the introduction of antibiotic stewardship programs. However, our results indicate that antibiotic prescribing can also be reduced through policies that encourage ACO participation and potentially other actions that encourage quality care and efficiency in the delivery of medical services through increased physician coordination and accountability. In addition to improving healthcare quality and reducing medical costs, ACOs may play a role in enhancing patient and public health safety through better antibiotic utilization.

Appendix A: Additional Data Details

Table 4.5.
Summary Statistics

	All		Prescribers	
Variable	**Mean**	**SD**	**Mean**	**SD**
Antibiotic Claims	72.48	129.82	104.52	144.76
ACO Participation	0.27	0.44	0.28	0.45
Physician Affiliations				
Number of Practices	1.15	0.55	1.15	0.54
Number of Hospital Affiliations	1.94	1.50	2.08	1.48
Number of Practice Members	361.64	695.30	330.70	661.89
Physician Characteristics				
Top Medical School Indicator	0.13	0.34	0.13	0.33
Uses Electronic Health Records	0.35	0.48	0.36	0.48
Experience	20.97	12.70	20.90	12.57
Female Physician Indicator	0.39	0.49	0.39	0.49
Patient Characteristics				
Average Age of Part B Ben.	71.14	5.38	71.79	4.44
Average Risk Score of Part B Ben.	1.65	0.80	1.65	0.80
Number of Female Part B Ben.	210.00	242.75	215.04	218.22
Low-Income Sub. Part D Claims	917.37	2,512.18	1,139.97	2,913.90
Low-Income Sub. Replace Ind.	0.07	0.26	0.03	0.18
Other Controls				
Number of Part D Claims	2,141.94	3,953.71	2,687.16	4,521.36
Cost of Part D Claims	225,097.45	455,652.46	262,304.76	491,758.62
Total Part B Services	3,287.50	17,347.67	3,903.08	20,134.50
Total Charges for Part B Services	396,063.82	899,358.90	405,719.78	910,958.75
Part B Ben. Receiving Services	370.99	436.69	379.65	393.41
N	1,120,690		777,172	

Appendix B: First-Stage Probit Results

Table 4.6.
First-Stage Probit Regression Results

VARIABLES	Full (1)	Prescribers (2)
Physician Affiliations		
Number of Practices	0.260***	0.265***
	(0.003)	(0.004)
Number of Hospital Affiliations	0.030***	0.021***
	(0.001)	(0.002)
Number of Practice Members	0.000***	0.000***
	(0.000)	(0.000)
Physician Characteristics		
Top Medical School Indicator	-0.009*	-0.000
	(0.005)	(0.006)
Uses Electronic Health Records	0.329***	0.352***
	(0.004)	(0.005)
Female Physician Indicator	0.058***	0.059***
	(0.004)	(0.005)
Experience	-0.007***	-0.008***
	(0.000)	(0.000)
Patient Characteristics		
Average Age of Part B Ben.	0.008***	0.005***
	(0.000)	(0.001)
Average Risk Score of Part B Ben.	-0.018***	-0.034***
	(0.003)	(0.003)
Number of Female Part B Ben.	-0.000***	0.000
	(0.000)	(0.000)
Low-Income Sub. Part D Claims	-0.000***	-0.000***
	(0.000)	(0.000)
Low-Income Sub. Replace Ind.	-0.106***	-0.231***
	(0.007)	(0.011)
Quantity of Services		
Number of Part D Claims	0.000***	0.000***
	(0.000)	(0.000)
Cost of Part D Claims	-0.000*	-0.000
	(0.000)	(0.000)
Total Part B Services	-0.000**	-0.000
	(0.000)	(0.000)
Total Charges for Part B Services	-0.000***	-0.000***
	(0.000)	(0.000)
Part B Ben. Receiving Services	0.000***	-0.000
	(0.000)	(0.000)
Observations	1,120,690	777,172
Specialty FE	YES	YES
Year FE	YES	YES
HRR FE	YES	YES
RUCA FE	YES	YES

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix C: Robustness Check - Censored Maximum Likelihood Estimates

Within the main analysis we impute the mean value for any censored outcome variable. However, to assesses the robustness of this approach we also estimate a maximum likelihood model that allows us to directly account for censoring within the specification of the likelihood function (a la Wooldridge (2010)). Results from the maximum likelihood model are provided within Table 4.7, along with the full-sample results reported within Table 4.3. Comparing the results we note that that they are almost identical, indicating no meaningful difference between our imputation approach and the maximum likelihood approach.

Table 4.7.
Censoring: Imputation and Maximum Likelihood Results Comparison

	All Impute (1)	All Impute (2)	All ML (3)	All ML (4)
ACO Participation	-2.556***	1.281***	-2.563***	1.277***
	(0.222)	(0.266)	(0.221)	(0.264)
ACO x Internal Medicine		-14.53***		-14.527***
		(0.620)		(0.617)
ACO x Family & General Practice		-12.37***		-12.339***
		(0.678)		(0.676)
ACO x Nurse Practitioner		4.394***		4.416***
		(0.559)		(0.554)
Observations	1,120,690	1,120,690	1,129,773	1,129,773
Specialty FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R^2	0.629	0.630	0.620	0.620

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix D: Robustness Check - Estimation Results for Separate Years

Table 4.8.
Effect on Antibiotic Claims (2016) - OLS Estimation Results

	All	All	Prescribers	Prescribers
	(1)	(2)	(3)	(4)
ACO Participation				
ACO Participation	-2.957***	0.512	-5.460***	-2.049***
	(0.274)	(0.334)	(0.359)	(0.534)
ACO x Internal Medicine		-12.28***		-9.449***
		(0.709)		(0.855)
ACO x Family & General Practice		-11.37***		-9.246***
		(0.787)		(0.900)
ACO x Nurse Practitioner		5.534***		6.154***
		(0.678)		(0.876)
Physician Affiliations				
Number of Practices	0.338	0.398*	0.624*	0.696**
	(0.220)	(0.220)	(0.342)	(0.342)
Number of Hospital Affiliations	1.425***	1.398***	1.758***	1.740***
	(0.119)	(0.119)	(0.190)	(0.190)
Number of Practice Members	-0.000450**	-0.000606***	-0.00192***	-0.00201***
	(0.000182)	(0.000182)	(0.000281)	(0.000281)
Physician Characteristics				
Top Medical School Indicator	-2.810***	-2.755***	-3.636***	-3.595***
	(0.324)	(0.324)	(0.457)	(0.456)
Uses Electronic Health Records	-5.958***	-5.774***	-7.878***	-7.667***
	(0.296)	(0.295)	(0.416)	(0.417)
Female Physician Indicator	-4.504***	-4.423***	-5.834***	-5.736***
	(0.273)	(0.272)	(0.408)	(0.408)
Patient Characteristics				
Average Age of Part B Ben.	1.366***	1.353***	1.151***	1.148***
	(0.0330)	(0.0329)	(0.0672)	(0.0672)
Average Risk Score of Part B Ben.	-2.666***	-2.661***	-3.060***	-3.041***
	(0.201)	(0.201)	(0.283)	(0.282)
Number of Female Part B Ben.	-0.0542***	-0.0536***	-0.0696***	-0.0694***
	(0.00722)	(0.00721)	(0.0119)	(0.0119)
Low-Income Sub. Part D Claims	-0.00145***	-0.00153***	-0.00113**	-0.00118**
	(0.000453)	(0.000453)	(0.000491)	(0.000491)
Low-Income Sub. Replace Ind.	-13.78***	-13.62***	-24.76***	-24.38***
	(0.230)	(0.230)	(0.531)	(0.530)
Quantity of Services				
Number of Part D Claims	0.0240***	0.0241***	0.0238***	0.0238***
	(0.000204)	(0.000204)	(0.000232)	(0.000232)
Cost of Part D Claims	-0.0000125***	-0.0000125***	-0.00000624***	-0.00000628***
	(0.000000781)	(0.000000780)	(0.000000947)	(0.000000947)
Total Part B Services	0.000174***	0.000174***	0.0000811***	0.0000818***
	(0.0000167)	(0.0000167)	(0.0000223)	(0.0000223)
Total Charges for Part B Services	0.000000123	0.000000152	0.000000738	0.000000769
	(0.000000290)	(0.000000290)	(0.000000546)	(0.000000546)
Part B Ben. Receiving Services	0.0449***	0.0446***	0.0732***	0.0731***
	(0.00417)	(0.00417)	(0.00585)	(0.00585)
Observations	526,001	526,001	365,431	365,431
Specialty FE	YES	YES	YES	YES
Year FE	NO	NO	NO	NO
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R^2	0.646	0.647	0.637	0.637

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.9.
Effect on Antibiotic Claims (2017) - OLS Estimation Results

	All	All	Prescribers	Prescribers
	(1)	(2)	(3)	(4)
ACO Participation				
ACO Participation	-2.323***	1.816***	-4.408***	0.312
	(0.262)	(0.305)	(0.346)	(0.467)
ACO x Internal Medicine		-16.86***		-14.60***
		(0.730)		(0.854)
ACO x Family & General Practice		-13.30***		-11.67***
		(0.780)		(0.869)
ACO x Nurse Practicioner		3.378***		3.428***
		(0.641)		(0.819)
Physician Affiliations				
Number of Practices	0.971***	1.040***	0.798**	0.882***
	(0.215)	(0.215)	(0.322)	(0.323)
Number of Hospital Affiliations	0.826***	0.807***	1.338***	1.325***
	(0.126)	(0.126)	(0.219)	(0.219)
Number of Practice Members	-0.000222	-0.000349**	-0.00121***	-0.00129***
	(0.000169)	(0.000170)	(0.000282)	(0.000282)
Physician Characteristics				
Top Medical School Indicator	-2.665***	-2.587***	-3.464***	-3.391***
	(0.327)	(0.327)	(0.459)	(0.459)
Uses Electronic Health Records	-8.095***	-7.727***	-10.70***	-10.25***
	(0.320)	(0.320)	(0.464)	(0.464)
Female Physician Indicator	-4.785***	-4.696***	-6.850***	-6.735***
	(0.261)	(0.260)	(0.409)	(0.408)
Patient Characteristics				
Average Age of Part B Ben.	1.324***	1.315***	1.013***	1.015***
	(0.0342)	(0.0340)	(0.0773)	(0.0771)
Average Risk Score of Part B Ben.	-5.261***	-5.290***	-5.650***	-5.661***
	(0.179)	(0.179)	(0.260)	(0.259)
Number of Female Part B Ben.	-0.0444***	-0.0435***	-0.0495***	-0.0492***
	(0.00700)	(0.00700)	(0.0110)	(0.0110)
Low-Income Sub. Part D Claims	-0.00378***	-0.00389***	-0.00370***	-0.00377***
	(0.000571)	(0.000567)	(0.000637)	(0.000634)
Low-Income Sub. Replace Ind.	-17.29***	-17.16***	-25.97***	-25.68***
	(0.235)	(0.234)	(0.554)	(0.553)
Quantity of Services				
Number of Part D Claims	0.0249***	0.0249***	0.0249***	0.0249***
	(0.000207)	(0.000206)	(0.000248)	(0.000248)
Cost of Part D Claims	-0.0000128***	-0.0000128***	-0.00000658***	-0.00000666***
	(0.000000853)	(0.000000849)	(0.00000108)	(0.00000107)
Total Part B Services	0.000181***	0.000182***	0.000112***	0.000113***
	(0.0000165)	(0.0000165)	(0.0000231)	(0.0000230)
Total Charges for Part B Services	-9.42e-08	-5.50e-08	0.000000376	0.000000422
	(0.000000306)	(0.000000305)	(0.000000722)	(0.000000720)
Part B Ben. Receiving Services	0.0421***	0.0417***	0.0637***	0.0636***
	(0.00407)	(0.00407)	(0.00620)	(0.00620)
Observations	594,689	594,689	411,741	411,741
Specialty FE	YES	YES	YES	YES
Year FE	NO	NO	NO	NO
HRR FE	YES	YES	YES	YES
RUCA FE	YES	YES	YES	YES
R^2	0.614	0.614	0.604	0.605

Robust standard errors in parentheses. Clustered at physician level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix E: Robustness Check - Propensity Score Matching Results

Figure **??** shows the propensity score distributions for the treated (dark-gray) and the untreated (light-grey).[19] This shows that we have common support for the propensity scores. In terms of establishing balance pre- and post-propensity score matching, Figures **??** and **??**, show that we have good balance for majority of the controls post matching. Lastly, Table 4.10 presents average treatment effect on treated results from the propensity score matching. Column (1) shows the ATT results for the full sample, while column (2) presents the results for the prescribe sub-sample. In terms of magnitudes, these are found to be similar to the estimates obtained with OLS.

[19]These propensity scores are based on Probit regression results that use the same controls as our other results within the paper.

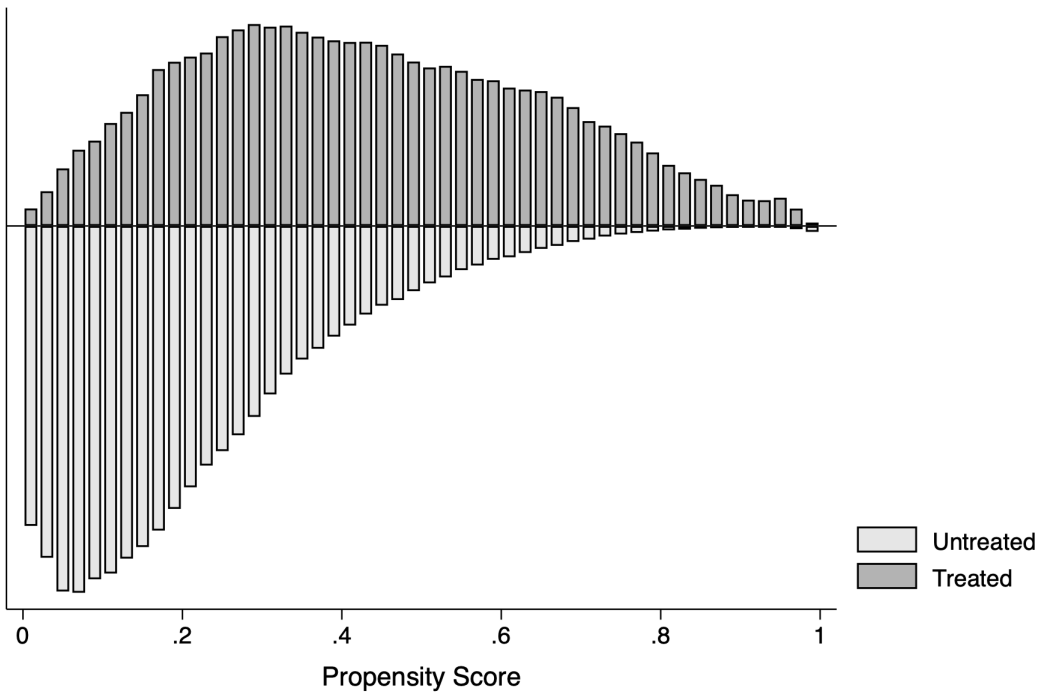

Figure 4.2. Propensity Score Distributions

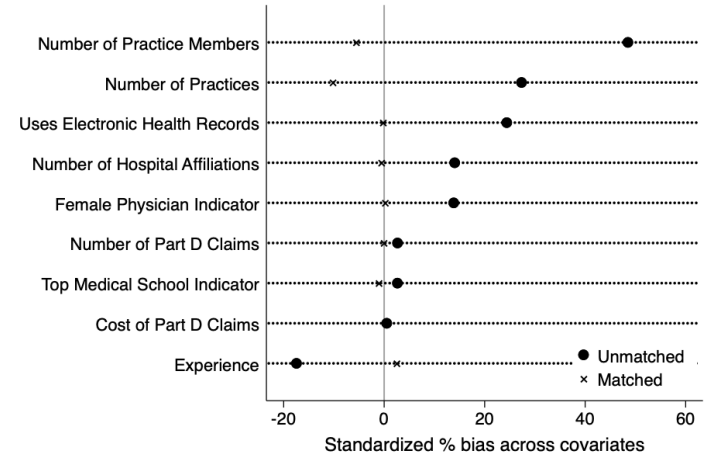

Figure 4.3. Balance Pre- and Post-Propensity Score Matching: Physician Affiliations and Characteristics

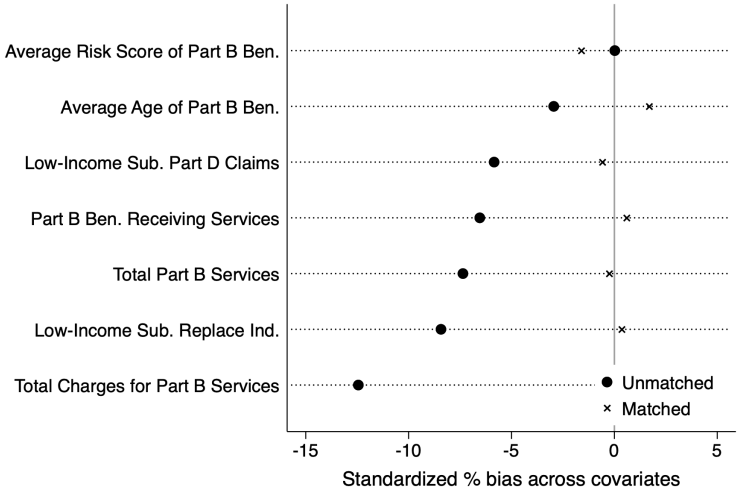

Figure 4.4. Balance Pre- and Post-Propensity Score Matching: Patient Characteristics and Volume

Table 4.10.
Average Treatment Effect on the Treated (ATT) Results

	Full	Prescribers
	(1)	(2)
ATT	-3.248***	-4.237***
	(0.467)	(0.595)

Propensity scores computed using probit regression.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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2015 MS in Economics, University of North Texas

2012 BBA in Economics, University of North Texas

Current position

Ph.D. Candidate, Purdue University, West Lafayette

Areas of specialisation

Health Economics; Industrial Organization; Applied Microeconometrics

Research Experience

2017-2020 Research Assistant to Ralph Siebert, Purdue University

2016-2018 Research Assistant to Anson Soderbery, Purdue University

2013-2014 Research Assistant to Janice Hauge, University of North Texas

2013-2014 Research Assistant to Todd Jewell, University of North Texas

Teaching Experience

2017 International Trade, Instructor, Purdue University

2015 Microeconomics (Recitation), Instructor, Purdue University

2015 Principles of Microeconomics, Instructor, University of North Texas

2014 Principles of Microecnomics, Instructor, University of North Texas

2015-2020 Various Courses, Teaching Assistant, Purdue University

2012-2015 Various Courses, Teaching Assistant, University of North Texas

Other Experience

2019 Summer Associate, Cornerstone Research, Washington D.C.

2007-2010 Sergeant, Team Leader and Vehicle Commander, U.S. Army

2005-2007 Rifleman, U.S. Army

Grants, honours & awards

2018 Krannert Research Symposium Top Presentation (runner-up)

2015 Krannert Certificate for Outstanding Recitation Teaching

2015-2016 Purdue Doctoral Fellowship

2014 University of North Texas Economics Faculty Scholarship

Publications & talks

Working Papers

2020 The Effect of Bargaining Power Determinants on Pharmaceutical Prices (with Sebastian Linde and Ralph Siebert), *Job Market Paper*

2020 Price Variation in the Retail Pharmaceutical Market: Evidence from New Hampshire (with Günter Hitsch, Sebastian Linde, and Ralph Siebert)

2020 Accountable Care Organizations and Physician Antibiotic Prescribing Behavior (with Sebastian Linde and Svetlana Beilfuss)

Conference Presentations

2019 Southern Economic Association, Ft. Lauderdale, FL

2019 Midwest Economic Association, St. Louis, MO

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