2011

PRICE LEVELS AND DISPERSION WITH ASYMMETRIC INFORMATION

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PRICE LEVELS AND DISPERSION WITH ASYMMETRIC INFORMATION

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Business and Economics at the University of Kentucky

By
Tanmoy Bhattacharya

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Lexington, Kentucky

2011

ABSTRACT OF DISSERTATION

PRICE LEVELS AND DISPERSION WITH ASYMMETRIC INFORMATION

In the extensive literature on price dispersions that exists to date, there is a gap in the analysis of how market structure affects prices as well as the degree of dispersion in prices. Specifically, the literature is deficient in analyzing how price levels and price dispersion are affected by the number of firms operating in a market. I use secondary data to look at the prices of prescription drugs at the retail level in nine hundred and seventy pharmacies across one hundred and sixty five markets in Maryland and compare price dispersion across these brick and mortar pharmacies *as well as* across a separate set of pharmacies that only operate online. I compare online versus offline price dispersion, as well as price dispersion in purely offline markets from the structure of the market's context.

Stahl's (1989) theoretical model is used to formulate and test the hypotheses that an increase in the proportion of positive search cost consumers in a market will cause price levels to rise and price dispersion to initially increase and then decrease. Furthermore, in markets with the proportion of positive search cost consumers above a threshold level, an increase in the number of firms will also lead price levels to rise and price dispersion to initially increase and then decrease. Conversely, in markets with positive search cost consumers below the threshold level, an increase in the number of firms will lead to lower price levels, i.e. the competitive outcome.

For the analysis, I look at prices at the pharmacy level and price dispersion at the market level and determine the proportion of high search cost consumers for a specific pharmacy or a specific market relative to the other pharmacies and markets in the dataset. I find that a significant part of the differences in prices for a homogeneous prescription drug can be attributed to asymmetric information and that price dispersion is higher in markets with a greater number of firms, and price levels are higher in low income neighborhoods.

KEYWORDS: Asymmetric Information and Market Failure, Price Dispersion, Search Costs, Prescription Drug Prices, Market Structure and Prices

PRICE LEVELS AND DISPERSION WITH ASYMMETRIC INFORMATION

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Date

DEDICATION

I dedicate this dissertation mostly to my parents, Mr. Tarak Nath Bhattacharya and Mrs. Supriya Bhattacharya, who emphasized the importance of a good education, and the value of hard work and persistence, and mildly less so to my sister, Mrs. Chandrima Mazumdar, thanks to whom I will always have unconditional love in my life.

ACKNOWLEDGEMENTS

I would like to thank a number of people whose help was indispensable in finishing this dissertation. Dr. Frank Scott, my dissertation chair, Dr. William Hoyt and Dr. John Garen, members of my committee, all of whom went out of their way to ensure the completion of this work. Without their valuable feedback and thorough guidance, this work would not have reached its culmination. I also owe a great deal of thanks to Dr. Karen Blumenschein, Dr. Chris Jepsen, Dr. Chris Talbert and Dr. Chris Bollinger for their help along the way.

In addition, I would like to thank Hannah Bhattacharya, who was a source of tremendous strength for a significant portion of the process.

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1. Introduction

With his lemons model, Akerloff (1970) showed how asymmetric information can lead to a lower average quality in the market for used goods. Research on market failures due to asymmetric information has advanced significantly in the last four decades. We see that car dealerships have taken notice and addressed the lemons problem via warranties for used automobiles. This is a market based solution to a failure in a market for a private good, and one preferred by most economists over government rules or regulations.

There are a number of states that have started to post retail prices of prescription drugs on a website typically maintained by the department of health or the state attorney general. New York originally passed legislation that required pharmacies to post the prices of a number of the most common drugs on a board at the pharmacy itself. The implementation of this type of policy in a number of states suggests that price shopping for prescription drugs may be warranted. This type of information asymmetry leads to distorted outcomes in what would otherwise be a competitive market. With an eye on Pareto efficiency, I look at prescription drug prices at the retail level, and observe high variance in these drug prices. I find that a significant amount of the variance can be attributed to information asymmetries and prescribe a highly publicized policy that makes prescription drug prices transparent to consumers, thereby promoting competition.

Despite an extensive literature on price dispersion, there has been little research on how market structure affects price levels as well as the degree of dispersion in prices. Specifically, the literature is deficient in analyzing how price levels and price dispersion are affected by the number of firms operating in that market. I use secondary data to look at the prices of prescription drugs at the retail level in 970 pharmacies across 160 towns in Maryland and compare price dispersion across these brick and mortar pharmacies *as well as* across a separate set of pharmacies that only operate online.[1] Testing hypotheses based on the theoretical predictions by the Stahl (1989) model, I find that price levels as well as price dispersion are higher in markets with a higher proportion of positive search cost consumers. I also find that as the number of firms in a market increases, the minimum price decreases. Surprisingly, I also find that price dispersion as well as the maximum price increases with a higher number of firms in the market.

There is a growing field of research examining dispersion in the prices of homogenous goods. Price dispersion observed in the prescription drug market has been a source of considerable interest as has been studying price dispersion of various goods sold online. However, the studies that look at pricing of prescription drugs focus almost exclusively on manufacturer or wholesale level price data (Danzon and Furukawa, 2004), or aggregate data when comparing across countries (Buzzelli, et al, 2006). Few studies look at *actual* retail prescription drug prices. For instance, Sorensen (2000) does so for only a few pharmacies in two small towns in the state of New York. Retail prescription drug prices are extremely time-consuming to gather and consequently, analysis of the pricing of the retail prescription drug industry is cost prohibitive. Average wholesale prices (AWP), on the other hand, are relatively easy to gather since The Redbook published by Thomson Reuters is available for purchase at a reasonable price and publishes AWP for all prescription and over the counter drugs.[2] However, this measure of "wholesale" prices is flawed due to manufacturers and wholesalers drastically marking

[1] The online data is primary.
[2] The electronic version, on the other hand, is quite expensive.

up this price. According to a 2005 report published by the Department of Health and Human Services (Levinson, 2005), the difference between the average wholesale price and the average sale price (which is defined as the actual sale price to retailers net of all discounts) for 2077 national drug codes is forty-nine percent i.e. AWPs are listed at 49% above the average sale price. A lot of states base their Medicaid payments on the AWP, and so marking up these prices results in a higher payout for the drug industry.

In the data used in this study, it is possible to pay several times as much for the same identical prescription drug at one pharmacy as opposed to another.[3] However, the mean of the coefficient of variation for all drugs is a more reasonable 14.38% (the mean of the coefficient of variation for all drugs was calculated by computing the coefficients of variation for each individual drug and then finding the average of this measure). I also look at prices online as well as prices offline and compare the spread in prices across online retailers as opposed to offline retailers. The intuition behind this analysis is that search cost for goods shopped online are close to zero whereas search costs for goods in traditional brick and mortar stores are relatively high. Therefore, consumers are more likely to search across various retailers online than they are offline. I test the hypothesis that prices across brick and mortar stores should be more dispersed than prices across online stores. The driving force behind the relatively higher observed price dispersion across offline retailers is the asymmetric nature of the information about prices that are available to consumers. Consumers shopping for prescription drugs online are better informed about the distribution of prices than are consumers shopping offline.

[3] I took the maximum price of each drug across all pharmacies in Maryland and divided it by the minimum price of the same drug across the entire state. This maximum to minimum ratio for each drug is discussed in greater detail in chapter 4. The average for this ratio across all drugs was an astounding 3.45 i.e. a consumer unlucky enough to walk into the highest priced drug store for each drug would pay an average of 345% the price that they would if they walked into the lowest priced store instead.

In a separate analysis, I look at prices and price dispersion for pharmaceuticals in each of the one hundred and sixty municipalities in Maryland and look at market-specific as well as drug-specific characteristics to see if they have any impact on the level of price dispersion observed. I compare prices at brick and mortar pharmacies with a larger proportion of Medicaid patients to prices at brick and mortar pharmacies with a relatively smaller proportion of Medicaid patients. This measure is computed by constructing a simple index in which the number of the type of prescription drugs sold by each pharmacy is weighed by the popularity of the prescription itself. The intuition behind this measure is in that pharmacies selling to relatively more Medicaid patients would also be selling to more consumers who do not qualify for Medicaid but are also unable to afford prescription drug coverage.[4] These consumers have high search costs relative to consumers with prescription drug coverage who are essentially zero search cost consumers.

Based on Stahl (1989), I expect prices to be higher in markets with a higher proportion of positive search cost consumers, and price dispersion to be either higher or lower, depending on the number of pharmacies in the market. Perhaps the most interesting prediction of this model is that given a threshold proportion of positive search cost consumers, as the number of stores increase, the expected prices increase. The intuition is that as the number of stores increases, the probability of being the low price store that positive search cost consumers stumble upon declines. Therefore, in a population with a sufficiently low proportion of zero search cost consumers, an increasing number of stores can actually lead to higher prices. This result is particularly

[4] To qualify for Medicaid in Maryland, income for the individual has to be less than $350 per month *and* assets cannot be worth more than $2500.

interesting since it runs counter to the standard result in microeconomic theory whereby an increase in the increase in the number of sellers will result in greater competition in the market, which should lead to lower prices. The underlying assumption of perfect information, i.e. all consumers have zero search costs, is the key difference that drives the divergent results in the competitive outcome as opposed to the Stahl model.

Furthermore, pricing of pharmaceuticals at the retail level seems to be driven largely by demand side factors. For example, 30 tablets of Lipitor 10 milligram (mg) in July 2010 on drugstore.com cost $95.99. When I look at the 20 mg version, the price increases to $135.99. This could be due to various production issues like active ingredient costs, etc. However, 30 tablets of 40 mg as well as 80 mg strength Lipitor also cost $135.99. It appears to be the case that a fairly significant part of the pricing strategy is more consistent with addressing informed consumer behavior such as pill-cutting[5] as opposed to active ingredient cost. Since the 10 mg dosage is the most common form prescribed, individuals willing to buy a higher dosage and cutting the pill, pay the same price for all the higher dosage forms. Although I use Lipitor as an example since it is the number one selling prescription drug in the country,[6] this pricing strategy of equal prices for higher dosages is the norm as opposed to the exception.

The rest of the dissertation is organized as follows. Chapter Two reviews the literature in the area while Chapter Three presents the theoretical framework based on Stahl (1989). Chapter Four describes the data, Chapter Five presents the empirical model

[5] Pill-cutting is a growing trend to the extent that there are pill cutters now available for specific drugs to conform to the shape of the pill i.e. drug specific pill cutters are widely available at retail outlets as well as web sites such as pillcutter.com.
[6] Table A.1 in Appendix.

and some econometric issues, Chapter Six states the results and follows up with some extensions to the baseline model, and Chapter Seven concludes this dissertation.

2. Literature Review

The literature on price dispersion is well established and in the last few years there has been considerable interest in search theory due to the proliferation as well as the use of the internet to conduct searches for price and product information. Although there are quite a few studies on the impact that online shopping has had on price dispersion of products, there are a limited number of studies on price dispersion observed in the retail prescription drug market. Even a Congressional Research Service Report by Austin and Gravell (April 2008), points out the necessity for research in this area. A number of well thought out studies have paved the way for the analysis conducted in this dissertation and are summarized below.

2.1 Theoretical Literature

A lot of work has been done explaining price dispersion from a theoretical context. I observe models explaining dispersion for both homogeneous as well as heterogeneous goods. I focus on price dispersion in homogeneous goods since this particular phenomenon must be the result of some friction in the marketplace. Retailers selling homogeneous goods in competitive markets are able to sell these goods at varying prices. In spite of many sellers and many buyers, I don't observe the Bertrand result. There is a great deal of price dispersion discernible for homogeneous goods that are sold offline as well as online. This is somewhat puzzling since basic principles of microeconomics dictate that in competitive markets, prices will converge toward marginal cost. I summarize below some of the theoretical models that explain how it is possible to observe persistent price dispersion in the type of market outlined above.

Search theory, first developed in Stigler (1961), has grown considerably over the decades. Stigler observed that prices for homogeneous goods exhibited considerable and persistent dispersion and was astute in making the distinction with price discrimination. While search theory is based on imperfect information, price discrimination results due to heterogeneous consumer preferences or characteristics. Since Stigler, a number of other researchers have advanced the theoretical literature in this area and shown why prices for homogenous goods can be dispersed across extended periods of time. Salop and Stiglitz (1977) show that with two sets of consumers, those who are perfectly informed about prices and those who are not at all informed about prices, it is possible for some stores to charge a low price and for other firms to charge a high price over the long run. Varian (1980) began his paper with the now well-known statement "the law of one price is no law at all," and went on to show that stores would randomize their prices so that they could keep consumers from learning about the price distribution i.e. which stores charged low prices persistently. Carlson and McAfee (1983) show that while consumers have differing search costs, firms have differing production costs and thus, firms with lower marginal costs will charge a lower price. Burdett and Judd (1983) show that theoretically, price dispersion in the equilibrium is possible in spite of identical and rational buyers and sellers. The driving force behind their results is that search is "noisy" i.e. consumers may learn of two or more prices when they search but search is costly.

Some of the online retailers selling books have customized newsletters that a consumer who has made a purchase at their web sites can subscribe to. The consumer has to fill out demographic information and also the type of books that they are generally interested in. The newsletter then is sent to the consumer with offers of discounted prices on the types of books the consumer specified. These discounts are however, not available to someone who visits one of these web sites for the first time. Milgrom and Roberts (1986) point out that consumers who are interested in certain types of products are likely to be more informed about them, and thus have a better idea of what kind of prices they can get on these products. On the other hand, consumers who are purchasing this type of book for the first time may be doing so for the purpose of giving it as a gift and so are unlikely to have as much information on the price of the book. This type of third degree price discrimination allows the supplier to extract some consumer surplus.

Baye and Morgan (1) (2001) show that price dispersion will persist despite zero search costs brought about by the Internet because comparison-shopping agents will charge fees to both consumers and suppliers. The authors conclude that social welfare is maximized when there is competitive pricing in the market. However, this does not result in maximizing the gatekeeper's profits. In equilibrium, the gatekeeper's profits are maximized when fees charged to firms are set low enough so that all consumers subscribe, fees charged to firms are set high enough so that only some of the firms subscribe, and firms that subscribe to the gatekeeper's services set lower prices for the actual product than firm's that don't subscribe. In an extension to their own work, Baye and Morgan (2) (2001) show that when online retailers are able to distinguish between consumers in terms of who is accessing a shop-bot and who is accessing the retailers of the web-site directly, they price discriminate. Consumers who access the retailer's web-site directly are charged more than those who access through a shop-bot because the shop-bot makes available prices from the online retailer's competitors.

Lal and Sarvary (1999) develop a theoretical model to analyze markets for differentiated goods. They conclude that the Internet may lead to monopoly pricing if there is a large number of Internet users, physical attributes of the good which are non-communicable over the Internet are somewhat important, consumers are favorably inclined towards the brand they currently use, and when the fixed cost of a shopping trip is higher than the marginal cost of visiting additional stores. The results are driven by the key assumption that certain attributes of a product are only known to a consumer through physical inspection. As a result, consumers tend to exhibit loyalty to brands that they are familiar with rather than risk buying an unknown brand over the Internet. This increase in loyalty due to shopping over the Internet allows firms to behave as monopolies.

Developing a similar model, Janssen and Noll (2002) analyze markets where firms sell online and offline. The authors offer several interesting insights including showing that not all consumers who search buy because of certain uncertainties associated with carrying out a transaction online. Unless prices are low enough to compensate for these uncertainties, consumers will not purchase online. The model also shows that prices will be dispersed in the equilibrium. This is because certain stores charge a high price to profit from consumers who don't use the Internet and thus for whom it is costly to conduct search. Other stores charge a low price to attract consumers who do use the Internet. The authors show that marginal cost pricing never occurs in the equilibrium price distribution.

Arbatskaya (2000) conducts a theoretical analysis of consumers undertaking sequential search in a market where sellers are located in order. Thus to search a seller located at the bottom of the order, consumers have to pass all the sellers located above this particular seller. The order could be in the form of recommendations from a referral service such as a shopping agent. The model shows that higher prices are charged by sellers located at the entrance of the market. Therefore, consumers with lower reservation prices search longer and pay less for a homogeneous product than the consumers with higher reservation prices.

Greenwald and Kephart (1999) develop a theoretical model that establishes that increased usage of shopbots by consumers lead to a decrease in the average price of a commodity, as well as a decrease in the average profit earned by sellers. The authors predict that in the future, sellers may employ pricebots - adaptive, price-setting agents, in an attempt to gain an edge in the intensely competitive world of Internet commerce. The authors show that although pricebots might lead to price wars, its still possible for sellers to earn profits above the game-theoretic equilibrium levels.

Morgan and Sefton (2001) extend the Varian (1980) model of sales to show that prices are less competitive when the number of uninformed consumers are large, thus, even informed consumers end up paying more. Chen and Sudhir (2001) argue that "competition may be reduced and prices rise as consumer search costs for prices fall," due to the Internet. The authors show that this is theoretically possible and provide the intuition that while the Internet facilitates consumer search, it also enables firms to keep track of consumer behavior. In a brick and mortar type setting, firms are unable to distinguish between consumers who buy after conducting search and those who buy because of loyalty to the firm (or because they have high opportunity costs). However, online firms can track consumers and send them e-mails with special offers if they find that these consumers are price elastic. On the other hand if consumers are price inelastic, then they can be charged a higher price. This then leads to increased price dispersion in the equilibrium in spite of reduced search costs.

Carlson and McAfee (1983) show in a theoretical setting the existence of equilibrium price dispersion for a homogeneous good. The driving force in obtaining the results are the assumptions that firms have varying production costs and consumers have differing search costs. The main predictions of this model are that:
(a) firms with lower costs of production will charge lower prices and have higher demand for their product, (b) consumer search may result in demand being a linear function of the difference between the firm's prices and the average price set by all firms, (c) profits will be proportional to the square of quantity demanded, (d) cost functions of potential firms will determine the number of firms in equilibrium and the larger the range of consumer search costs, the greater the number of firms in the market, (e) the variance of a firm's costs results in directly influencing the variance of prices offered by firms, (f) an increase in the number of firms, decrease in the slope of the marginal cost functions, or decrease in the density of distribution of consumer search costs will result in an increase in the variance of prices, and (g) a proportional tax will also increase the variance of prices because it will not be completely passed on to the consumer.

Burdett and Judd (1983) show that theoretically price dispersion in the equilibrium is possible in spite of identical and rational buyers and sellers. The driving force behind their results is that search is "noisy" i.e. consumers may learn of two or more prices when they search but search is costly. Fishman (1992) analyzes a theoretical model to show that when buyers are imperfectly informed and it is costly for sellers to change prices, staggered price-adjusting will emerge. Thus, the author suggests that price dispersion is a real effect resulting from inflation.

Keller and Rady (2003) show that when consumers sometimes view the product as similar and sometimes as differentiated, there is an opportunity for a duopoly to acquire information on consumer behavior. The authors develop a theoretical model that shows that when information is of low value to firms, they charge the same price. However, if information has high value, then firms learn by creating price dispersion.

Macminn (1980) extends Stigler's (1961) and McCall's (1970) search models to show that it is possible for a price distribution to exist in the equilibrium. The author shows that in the Stigler model, the variance of the price distribution is a "monotonic increasing function of nonsequential search intensity," whereas in the McCall model, the variance of the price distribution is an eventually decreasing function of sequential search intensity.

Reinganum (1979) assumes that firms have heterogeneous marginal costs, which results in equilibrium price dispersion. However, in the book industry, a number of lawsuits have resulted in publishers being unable to price-discriminate between retailers – even volume discounts are not legal. Salop and Stiglitz (1976) use an overlapping generations model and heterogeneous consumer search costs to show equilibrium price dispersion. Salop's (1979) circular city model shows that even if products are homogeneous, positive consumer search costs will lead to higher than marginal cost pricing.

Stahl (1989) developed a model in which some consumers have zero search costs while others have positive search costs. He assumes that there are N identical stores selling a homogeneous product with constant marginal costs. Stahl shows that if all consumers have zero search costs then prices converge to marginal cost i.e. the Bertrand result, since all consumers will purchase from the lowest-priced store. Conversely, when all consumers have positive search costs, the price distribution converges to the monopoly price i.e. the Diamond result. This result holds under the assumption that the reservation price for all consumers is unique and the cost for additional search outweighs the benefits to be gained from the search.

Furthermore, the model shows that as the proportion of consumers with zero search costs goes from 0 to 1, the Nash Equilibrium price distribution changes continuously from the degenerate distribution at the monopoly price to the degenerate distribution at the competitive price. An interesting prediction of this model is that as the number of stores that offer the product increases, the NE becomes more monopolistic. This is obviously contrary to expectations in that we would expect the competitive market outcome but that would only hold with the presence of a sufficiently high proportion of consumes with zero search costs. The intuition is that as the number of stores in the market increases, the probability of being the lowest priced store decreases dramatically. Thus, the expected payoff is higher for charging captive high search cost consumers high prices, than it is for attracting zero search cost consumers by charging low prices. Given a market with a low proportion of zero search cost consumers, it will be more profitable to cater to the positive search cost consumers and charge higher prices.

2.2 Empirical Literature

2.2 (a) Price Dispersion in General

Brown and Goolsbee (2002) find that lower search cost through the Internet allow consumers to engage in low-cost price comparisons. Empirical work in their paper shows the impact of the rise of Internet comparison-shopping sites on the prices of new term life insurance policies. They observe that the growth of the Internet has reduced term life prices by 8 to 15 percent and increased consumer surplus by $115-215 million per year. They conclude that with the introduction of shop-bots, price dispersion initially increases, but as the share of people using this technology rises further, price dispersion falls.

Chandra and Tappata (2010) look at retail gasoline markets and find that price dispersion increases with search costs and also increases with the number of firms in a market. Anania and Nistico (2004) look at homogeneous food products across a number of retailers and observe that heterogeneity in retailer services as well as consumer search costs lead to sustained price dispersion. Nelson, Cohen and Rasmussen (2007) use data for books, computers and electronics and find that the level of price dispersion is positively correlated to the price of the product and the number of sellers, and lower for goods that would be bought repeatedly. They also find that sellers who offer low prices in one product, also typically offer low prices on all products.

Sorensen (2000) looks at two small towns in the state of New York and finds that in the market for prescription drugs, posted prices vary significantly across pharmacies in the same geographic market and pharmacy heterogeneity accounts for little of the price dispersion. He uses purchase frequency as a proxy for consumer search and finds that price dispersion of retail prescription drugs are lower when search intensity is higher and drugs for which consumers conduct more search have the lowest markup over cost. Our work is primarily different from Sorensen's in that while Sorensen used purchase frequency, a drug characteristic, to determine search outcomes, we use market characteristics – a significantly different approach. Furthermore, we take an in-depth look at price levels across geographic markets and analyze the impact of greater competition on prices of prescription drugs.

In a related study, Sorensen (2001) examines data from traditional brick and mortar pharmacies to infer that prices for prescription drugs vary widely across stores and while some stores may offer a particular drug at a low price, others offer a different drug at the low price – thus, one store does not consistently offer the low price for all drugs. On an average, the author estimates only 10 percent of consumers search for prices of prescription drugs and search is more intensive for a maintenance prescription drug i.e. one that is used repeatedly over time, than it is for a one-time purchase prescription drug. The returns to search would be higher for a prescription drug used repeatedly so this finding is consistent with theoretical expectations. Furthermore, the author estimates the cost of an exhaustive search for a particular drug to be $15 for the average consumer and also finds that females have substantially lower search costs than males.

A lot of the recent work on price dispersion focuses on goods sold online. Surprisingly, a good deal of the evidence shows that even for undifferentiated products such as books and CDs, price dispersion between online retailers is actually greater than traditional retailers (Brynjolfsson and Smith, 1999). This seems to be contrary to the perfect information assumption and the resulting implication that price dispersion among undifferentiated products should vanish. Additionally, menu costs, which are the costs of changing prices on products, are nearly zero for Internet retailers. This should further dissipate any price dispersions since price stickiness will be less of an issue.

Furthermore, Amazon.com, which has the biggest share of all books sold online (screen share of 80% - reported by Web21), practices price discrimination by giving special offers to consumers who have bought books from them before. New consumers who get on their web site for the first time to buy a book do not have access to this same offer. This type of pricing strategy implies mark-up pricing on the part of the suppliers. How this strategy is viable in spite of almost zero information costs and will it persist in the future are questions of interest to this author.

Brynjolfsson et al. (2006) estimate the benefits of searching lower screens for the median consumer to be $2.24 and the cost to be $2.03. An interesting result that they find is that consumers who are less price sensitive actually search more. They attribute this find to consumers placing greater importance on delivery time and reliability of the online retailer. They sum up that substantial price dispersion can exist in equilibrium in online markets because of heterogeneity in consumer preferences for price and non-price attributes of a product.

Gatti and Kattuman (2003) use data obtained from a major European price comparison web site to compare prices of products in five different categories across seven European countries. They find significant levels of price dispersion within countries as well as across product categories. Brynjolfsson et al (2007) find that by reducing search costs, online markets have enhanced consumer welfare in many ways including increasing the variety of products available. In particular, obscure products are more easily available to consumers and more people are buying these types of products online as opposed to through traditional channels.

Bayliss and Perloff (2002), analyze the online markets for cameras and scanners and find that there are "good firms" that charge a lower price and provide superior service while "bad firms" charge a higher price and a lower level of service. They imply that their findings are consistent with the Salop and Stiglitz model (1977), where firms with a bigger market share are able to provide better service and a lower price because of economies of scale.

Pan, Ratchford and Shankar (2002) analyze several markets of goods sold online to determine that price dispersion is significant even after controlling for web-site characteristics. They find that market characteristics, as opposed to firm characteristics, are major determinants of online price dispersion. They also find that price dispersion increases with an increase in the average level of prices but decreases with an increase in the number of competitors. Furthermore, the authors find that web-sites that offer better quality services do not necessarily charge a higher price. On a similar vein, Pan et al (2003) look at how prices online have evolved since the bursting of the Internet bubble in the early 2000's. They find that prices in online markets have been persistent over the period of their study from 2001 to 2003 and in some markets, it actually increased. In further research in this area Pan et al (2004) also show that in equilibrium, consumer heterogeneity in willingness to pay for retail service results in higher prices for brick and mortar as opposed to internet retailers. They find that brick and mortar retailers provide better service and charge higher prices which enables them to make greater profits.

Zettelmeyer, Scott Morton and Silvo-Risso (2006) conclude that online consumers pay an average of 1.2% less for a new car than consumers shopping through traditional channels. Furthermore, it is determined that after controlling for selection, consumers who use the online referral service, Autobytel.com, pay 2.2 % less. The authors estimate consumer surplus from the use of this one referral service alone to be $240 million per year. On the other hand, Clay, Krishnan and Wolf (2001) use data on prices of books sold online to empirically analyze price dispersion on the Internet. They find that there is no change in prices or price dispersion over the period of their study. They also find that advertised or popular items, such as best sellers on the New York Times bestseller list, have the lowest price relative to the publisher's suggested price. However, price dispersion for these items are high which is inconsistent with search theory. The authors suggest that the reason they don't observe a convergence in the price for what is essentially a homogeneous good is because online stores have succeeded in differentiating themselves.

In a similar paper, Clay et al. (2002) use data collected from online as well as brick and mortar book stores to determine that average prices for online as well as brick and mortar stores are similar. However, online stores exhibit significant price dispersion. They suggest that firms are trying to differentiate themselves in terms of non-price attributes such as providing reviews, recommendations, loyalty programs, etc. They also found that Amazon.com was charging a premium over rivals such as Barnesandnobles.com and Borders.com which implied that Amazon.com had succeeded in differentiating themselves from their rivals.

Cheng, June and Nault (2006) find that electronic markets have matured and if in a market with a number of existing retailers, there is a potential new entrant, then one of the existing retailers exist first when costs faced are similar. However, if the market is not covered by existing retailers, then the new entrant will enter the market if they have a slight Internet channel entry cost advantage. If the market is covered by existing retailers, then the cost advantage has to be larger for the potential new entrant to enter the market.

Ellison and Ellison (2006) find that electronic market purchases strongly correlate to the state and the state tax rate where the purchase is being made. They find that avoiding sales tax may be an important contributor towards consumer purchasing decisions between online and offline channels. They also find that consumers prefer buying from firms located in nearby states so that they can benefit from faster shipping times. Goldmanis, Hortacsu, Syverson and Emre (2008) look at travel agencies, bookstores, and new auto dealers to determine what industries are better off as an increasing number of consumers use the internet for shopping. They assume that consumers have lower search costs as a result of e-commerce and find that there is a reduction in the number of smaller business within this industry as market share is redistributed to bigger firms from these smaller firms.

Baye, Morgan and Scholten (2001) examine the market for electronic goods sold on the Internet and find that when fewer firms offer the same product for sale, price dispersion is greater whereas when a large number of firms offer the same product for sale, price dispersion is much smaller. They also find that prices on the Internet are not converging to the "law of one price." Clemons, Hann and Hitt (2000) find that online travel agents offer tickets with significantly different prices and characteristics when one unique customer request is submitted. After controlling for product differentiation, the authors determine that ticket prices differ by as much as 18% across online travel agents. The authors conclude that for the online market for travel agents, product differentiation is an important part of the pricing strategy, but there also appears to be a certain amount of random inefficiency.

Lehmann (2001) also analyzes the online travel agency market and determines that on an average, prices tend to be lower and more dispersed on the Internet. However, when the author controls for higher quality and lower quality products, he finds that goods of a lower quality tend to have a higher price and higher price dispersion on the Internet whereas goods of a higher quality have a lower price and lower price dispersion on the Internet. The author conjectures that this may be because there is greater incentive for consumers to search for higher priced items online since expected returns to search will be greater whereas for the lower priced items, consumers will tend to be less informed since expected returns to search will be lower.

Scott Morton, Zettelmeyer and Silvo-Risso (2001) analyze the market for new cars to determine that in traditional dealerships, African-American and Hispanic consumers pay around 2% more than other consumers. However, this premium, in part is explained by the differences in income, education and search costs. The authors also find that minority consumers buying new cars using an online referral service pay nearly the same prices as white consumers regardless of their income, education and search costs. In a related study, Zettelmeyer, Scott Morton and Silvo-Risso (2001) conclude that online consumers pay an average of 1.2% less for a new car than consumers shopping through traditional channels. Furthermore, it is determined that after controlling for selection, consumers who use the online referral service, Autobytel.com, pay 2.2 % less. The authors estimate consumer surplus from the use of this one referral service alone to be $240 million per year.

Smith and Brynjolffson (2001) find that online consumers are loyal to the retailers they purchase from and use the reputation of a retailer as a proxy for non tangible aspects such as shipping on time. They also determine that consumers respond to the allocation of the total price of a product between the item price, shipping costs and tax. The authors are able to identify each consumer with a cookie number. This enables them to conclude that certain consumers are more sensitive to changes in sales tax and shipping costs than they are to changes in the item price. In a closely related study, Brynjolffson and Smith (2001) find that besides price, brand name retailers and retailers from whom the consumer has purchased previously are important factors in determining the consumer's choice. Furthermore, allocation of total price among item price, shipping and tax is also important to consumers. Finally, the authors determine that consumers use the reputation of an online seller as a proxy for non-tangible aspects of the product such as shipping.

Ariely and Lynch (2001) set up an experiment in a laboratory type setting and show that for differentiated products like wines, consumer demand became more inelastic when information about quality was made available. On the other hand, consumers became more price sensitive when the search process was facilitated. Lowering search costs resulted in welfare gains for consumers. Furthermore, when search was hard, market share for common wines was proportional to their share of the distribution of all wines sold, but when search was made easy, the market shares returns to distribution declined.

Cason and Friedman (2000) simulate markets with varying search costs in a laboratory setting. Buyers observe either one or two of the posted prices at zero search cost. Buyers then either accept that price or search again but this time at a cost, or drop out of the market. Consistent with equilibrium theory, the authors determine that transaction prices converge to a “very low price” when search costs are zero and converge to a “very high price” when search costs are very high. Specific price distributions are also found to exist when search costs are positive but not prohibitive.

Carlton and Chevalier (2001) analyze data on sales of fragrances, DVD players and side-by-side refrigerators both from traditional outlets as well as online. They find that manufacturers who limit distribution of their products to traditional brick and mortar retailers also limit distribution to online retailers, particularly to online retailers who sell products at a high discount. Interestingly, the authors also find manufacturer websites charge high prices and don’t appear to be undercutting the prices offered by Internet retailers. Ping, Lee and Yan (2000) show that online markets for books are more competitive than brick and mortar markets using an indirect approach. They hypothesize and provide empirical evidence to show that switching costs are lower for online consumers as a result of which discounts on bestsellers are relatively smaller than they are at brick and mortar stores.

Kauffman and Wood (2000) find that prices for goods sold online don’t converge to marginal cost because the Internet enables competitors to tacitly collude by keeping tabs on their rival’s price changes instantaneously. A reaction by competitors in lowering their price immediately in response to a firm lowering its price negates any profits that could be obtained from increased market share. Thus, firms don't have any incentive to lower their prices and this keeps prices from converging to marginal cost. In a similar study, Kauffman and Wood (2001) hypothesize that electronic commerce technology enhances the ability of firms to keep prices higher by tacit collusion in spite of a highly competitive environment. The empirical results show that firms may either tacitly collude or compete depending on characteristics of the industry and the firm.

Anand and Shachar (2000) estimate how much information consumers have about product attributes and the impact it has on brand loyalty. They determine that when consumers don't have complete information about a product's attributes, an individual's choice for a product is a function of the attributes of other products offered by the same brand. They also determine that the influence of brand image is lower for informed consumers and greater when brand image increases. Finally, the authors find that lack of information contributes to brand loyalty as opposed to "emotional attachment" to various brands.

Zettelmeyer, Scott Morton and Silvo-Risso (2006) conclude that online consumers pay an average of 1.2% less for a new car than consumers shopping through traditional channels. Furthermore, it is determined that after controlling for selection, consumers who use the online referral service, Autobytel.com, pay 2.2 % less. The authors estimate consumer surplus from the use of this one referral service alone to be $240 million per year. According to Srinivasan and Ratchford (1991), consumers will weigh cost and benefits of search for prices and this will effect their price elasticity. The benefits of search may include economic as well as psychological factors such as the enjoyment derived from shopping. The cost of search will include cost of searching for price as well as non-price attributes of a product. According to information search theory, the lower the expected benefits of information search, the lower is the price elasticity. Conversely, the higher the expected benefits of information search, the higher the price elasticity.

Cheng, June and Nault (2006) find that electronic markets have matured and if in a market with a number of existing retailers, there is a potential new entrant, then one of the existing retailers exit first when costs faced are similar. However, if the market is not covered by existing retailers, then the new entrant will enter the market if they have a slight Internet channel entry cost advantage. If the market is covered by existing retailers, then the cost advantage has to be larger for the potential new entrant to enter the market.

Ellison and Ellison (2006) find that electronic market purchases strongly correlate to the state and the state tax rate where the purchase is being made. They find that avoiding sales tax may be an important contributor towards consumer purchasing decisions between online and offline channels. They also find that consumers prefer buying from firms located in nearby states so that they can benefit from faster shipping times. Bailey (1998) found that prices on the Internet were typically higher than prices in traditional retail outlets.

Alba, et al (1997) suggest that the Internet could actually diminish price elasticity by allowing consumers to find products that best suit their needs. They find that when information about quality is important to consumers, interactive retailing lessens price sensitivity. Degeratu, Rangaswamy, and Wu(1999) used panel data from online grocery stores and found lower price elasticity for certain categories of products when information about these products were accessible for consumers. Choudhury, et al (1998) found that although the Internet can help consumers find better prices, it can also help producers extract consumer surplus. Lee (1998) found that a Japanese online auto auction service repeatedly realized higher prices than traditional auto auctions. Cortese and Stepaneck (1998) found several online markets that realize higher prices than their traditional counterparts.

2.2 (b) Prescription Drug Price Related Literature

Aronsson, Bergmann and Rudholm (2001) investigate the Swedish market for 12 brand name drugs to determine how market share for the brand name drugs are affected by the difference between the price of the brand name drug and the price for its generic substitute. They find that for 5 of the 12 brand name drugs, the average price of the generic substitute significantly affects the market share for the brand name drug. The larger the ratio of the brand name drugs price to the price of its generic substitute, the smaller the market share of the brand name drug.

Grabowski and Vernon (1992) determine that the difference in the prices of brand name drugs and their generic substitutes is the cause for the generics to capture a relatively large market share as soon as they are introduced to the market i.e. after the patent for the brand name drug expires. Caves, et al (1991) find that when generic substitutes enter the market, price for the brand name drugs decline significantly.

Costello (2000) looks at the reference price system which is in existence in most of Europe and designed to cut back on national pharmaceutical expenditure by replacing brand name drugs with their generic substitutes. The author develops a theoretical model for a duopoly to show that brand-name sellers will offset lower profits by selling higher quantities instead of charging a higher price. The driving force behind these results are the assumptions made about the introduction of the reference price system and a vertically differentiated model.

2.3 Government, News and Private Entity Reports

I further look at whether or not price dispersion for prescription drugs for the elderly have changed since the implementation of Medicare Part D prescription drug benefit plans. Medicare Part D plans are private plans that allow beneficiaries to enroll on a voluntary basis in these subsidized plans that cover prescription drug costs. According to The Medicare Factsheet (January 2010) published by the Kaiser Family Foundation, Medicare Part D accounts for 11% of benefits spending and has over 27 million enrollees. While not all pharmaceuticals are prescribed only to specific age groups, certainly drugs for Alzheimer's or Osteoporosis are highly likely to be used by the elderly as opposed to birth-control, which are not**.** I have looked at data collected in 2008 and 2009 for various "demographic specific drugs" and compared price markups to data collected in 2002. Medicare Part D was passed in 2003 and began in 2006. I am essentially looking at a market with a proportion of consumers with positive search cost evolving into a market where most consumers have zero search costs. This implication derives from the fact that a greater proportion of the elderly, without incurring any search costs, now enjoy the benefits of complete search since the insurance companies are now negotiating the prices for them. In 2002, roughly a third of all elderly were without any coverage for prescription drugs. That percentage, as of February 2010, stands at about ten. Coverage for prescription drugs here is defined as coverage by all plans under

Medicare Part C and D, and including the Department of Veterans Affair, the Federal Employees Health Benefits Program, Tricare, the Retiree Drug Subsidy.[7]

While research in the past (Buzzelli, et al, 2006) has considered the impact of the existence of generics on pricing of pharmaceuticals, I look at a bigger class of possible substitutes by looking at Therapeutic Equivalents. All generic drugs are therapeutically equivalent to their brand name counterpart. However, the converse is not true i.e. all therapeutically equivalent drugs are not just the generic version of the brand names. According to the FDA web site, all therapeutically equivalent drugs when administered under the conditions specified in the labeling are expected to have the same clinical effect and safety profile. Lipitor, a brand name drug and a statin for controlling cholesterol, does not have any generic substitutes but has a therapeutic equivalent in Zocor, also a brand name drug and a statin. Zocor does have a generic version in existence and physicians are substituting between Lipitor and the generic version of Zocor to the extent that Pfizer, the maker of Lipitor, has been heavily advertising and informing consumers that they should not switch if Lipitor works for them and the generic that they are switching to is not a generic version of Lipitor.[8]

It is important to note that we are looking at retail prices and not manufacturer or wholesale prices. Therefore, any of the standard arguments of higher pricing and higher profits leading to greater investments in research and development, which further lead to innovation are moot. Higher prices charged by pharmacies, however, may indeed lead to

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[7] Data for proportion of elderly covered by insurance for prescription drugs in 2002 and in 2009 were compiled from the Kaiser and Centers for Medicare and Medicaid web-sites.

[8] http://www.lipitor.com/patients/generics.aspx and http://davisliumd.blogspot.com/2009/04/generic-lipitor-not-yet-other-excellent.html

a smiling pharmacist as opposed to a frowning one. One would further conjecture that the smile on the pharmacist charging over a thousand percent of the price the lowest priced pharmacy is charging would have to be fairly… dazzling.[9] I think the timing of this particular dissertation would be difficult to beat. Health care costs are in the news to the extent that someone writing a dissertation in a related area needs write very little to justify why it would be a meaningful dissertation. Nevertheless, in the course of providing rationale for this research, it would be a disservice not to present the following facts pertinent to justifying the dissertation topic.

A Congressional Research Service Report called “Does Price Transparency Improve Market Efficiency? Implications of Empirical Evidence in Other Markets for the Health Sector” (Austin and Gravell, 2008) looks at a number of studies including a couple summarized in this outline and concludes that reforms that increase price transparency would reduce prices. They find that in the healthcare sector, there is a strong need for greater price transparency and consumers have difficulty finding useful price data. In the empirical studies that the report looks at, the two main avenues through which price transparency is attained are a) increasing price information in advertising and b) Internet comparison shopping sites. The study concludes that in spite of the healthcare sector being somewhat complicated due to characteristics such as qualitative differences in complicated products, payments made by some form of insurance, etc, greater price transparency could lead to more efficient outcomes and lower prices for consumers.

[9] As pointed out in footnote 3, the maximum to minimum ratios are presented in Table 4.2. The highest of these ratios are for Ortho Evra which sells at the highest priced pharmacy (priced at $357.90 at Ritchie Pharmacy in Brooklyn Park) at 10.26 multiple of the price at the lowest priced one (priced at $35.00 at The Homecare Pharmacy Fennel in Hagerstown).

"Prices will decline and brand loyalty will be threatened as both Internet startups and traditional retailers try to acquire and retain customers in a rapidly expanding medium of commerce. At the limit, prices will be driven down to marginal cost as a result of intense competition and perfectly informed consumers." (Saloner, et al, 2000). However, if one accesses an online comparison-shopping agent such as Pricescan.com, MySimon.com, Bizrate.com, deals4u.com, etc., one is confronted with a fairly wide array of prices for the exact same product such as a book or a CD or a DVD player or prescription drugs. These products are not identical in the sense that all medications are the same but rather in the sense that if one wanted to purchase a bottle of Centrum vitamins of a certain size, then *that* bottle of Centrum would take on the properties of a commodity product, being offered by various sellers. Furthermore, ISBN numbers for books, manufacturing numbers for electronics and computers, package size and strength of a prescription drug, etc, ensure that distinctions are made for different attributes and that the products being compared are indeed homogeneous. Thus, it is surprising indeed that with perfect information, many suppliers, and homogeneous products - all trademarks of a perfectly competitive market - price dispersion should exist. The purpose of this paper is to see if systemic price dispersion does indeed exist among on-line as well as traditional brick and mortar retailers and what reasons there could be for its existence.

The GAO (2009) looks at Average Wholesale Prices for prescription drugs between the years 2000 and 2008 and finds that a lack of competition mainly due to lack of therapeutic equivalents which could serve as substitutes was a consistent characteristic in 416 brand name prescription drug products which exhibit an “extraordinary price increase”. An “extraordinary price increase” is defined as an increase of one hundred percent or more at *any one point in time* across the period of the study. In over 90% of the cases, they found this increase to persist either at the increased price levels or bolstered by further increases. The GAO then proceeds to pick 6 drugs for a more detailed look. They state that corporate consolidations led to fewer choices through less competition and found four of the six drugs had their rights acquired by a new firm. Two of these drugs had an extraordinary price increase shortly thereafter.

According to the Congressional Budget Office, medical costs in the U.S. will increase from the current 16 percent to 25 percent of the nation's GDP by the year 2025, if they continue growing at their current rate of growth. That is quite the attention-getting statistic. However, with the health care insurance reform having just being signed into law, it will be interesting to see the actual outcome over the years. According to IMS, the World's largest pharmaceutical market, the U.S. grew by 1 to 2 percent in 2009, reaching $300.3 billion.[10] In comparison, Japan, the second largest pharmaceutical market in the World, grew by 4 to 5 percent and reached $84 to $88 billion. The U.S. is obviously a major player when it comes to the pharmaceutical market and the pricing of pharmaceutical drugs has been and will continue to be an important issue in this country for some time to come.

According to a New York Times article from December 3, 2008, about rising healthcare costs, "Celgene initially spent very little on research and priced each pill (of thalidomide) in 1998 at $6. As the drug's popularity against cancer grew, the company raised the price 30-fold to about $180 per pill, or $66,000 per year. The price increases

[10] Table A.1 in the appendix gives a breakdown of the pharmaceutical market over the last five years and includes the revenues generated by the top five selling drugs across those five years.

reflected the medicine's value, company executives said." The GAO report (2009) cited earlier states that this is a common reason stated by pharmaceutical firms as justification for an "extraordinary price increase."

Furthermore, due to a provision in the Medicare Part D prescription drug program signed into law in 2003, the federal government cannot negotiate with pharmaceutical companies for lower drug prices for Medicare. It is left up to the private insurance companies who provide coverage for those on Medicare prescription plans to negotiate with the pharmaceutical companies. While that may seem fair on the surface, private insurance companies lack the clout that a federal government agency could wield in terms of getting better prices for Medicare recipients since the Federal government would negotiate for all the private insurance companies. Additionally, Families USA, a consumer healthcare advocacy group, conducted a study in 2005 comparing drug prices under Medicare to those negotiated by the federal government for the Veterans Affairs (V.A.). Nineteen of the top twenty drugs prescribed were priced higher *under the lowest drug price* through any Medicare prescription plan. The median price difference for the top 20 drugs prescribed were 48.2% higher *under the lowest drug price* through any Medicare prescription plan as opposed to the V.A. plans i.e. 10 of the top 20 drugs prescribed had Medicare paying greater than 148.2% of what V.A. was paying. It is also important to note that while out of pocket expenses have decreased substantially over the years, they are still roughly a fifth of overall expenditures on prescription drugs. One must bear in mind that individuals without any kind of coverage have even less clout when it comes to negotiating healthcare costs and have traditionally paid a higher price for healthcare than any other group.

3. Theoretical Underpinning

3.1 Model

I use predictions from Stahl (1989) to formulate hypotheses for the purposes of empirical testing. To be clear, all of the theoretical implications presented in this chapter are borrowed directly from Stahl's model and adapted for the special case of shopping for pharmaceuticals and determining heterogeneous search costs via the measures defined in chapter 5. The model predicts that in a market for homogenous goods such as prescription drugs, as long as some proportion of consumers have positive search costs, some pharmacies will charge a low price while some will charge a high price. The model assumes that all pharmacies have identical costs and predicts that if all consumers have zero search costs, because, for instance, they all search using the internet, then prices converge to marginal cost since all consumers will purchase from the lowest-priced pharmacy. Conversely, when consumers have positive search costs that are prohibitive, because, for instance, all consumers have to physically visit the pharmacies to acquire price information, the price distribution converges to the monopoly price i.e. the Diamond result. This result holds under the assumption that the reservation price for all consumers is unique and the cost for additional search outweighs the expected benefits to be gained from search.

Suppose that all consumers have positive search costs, c, such that the c is greater than the expected benefits from search, i.e. the expected savings generated from search. I begin with a model in which there are two pharmacies located at opposite ends of a town. The model is similar to Hotelling's (1929) linear city model in that pharmacies are making location choices. However, while Hotelling addresses product differentiation with his model and hypothesizes that the firms will end up locating next to each other to minimize loss of market share, I look at heterogeneous consumer search costs and the impact it has on pricing decisions made by firms. If all consumers have prohibitively high search costs (they can observe the first price for free but incur a cost, c, if they wish to search for a second price), then the two pharmacies are effectively monopolies and consumers closer to pharmacy 1 will buy from it 1 while the consumers located closer to pharmacy 2 will buy from it. The firms will charge monopoly prices and maximize profits. Due to advances in technology, now suppose some proportion of consumers, $\mu \in [0, 1]$, who are able to acquire this technology can now search at zero cost i.e. they do not incur any cost when searching for the price of goods. When Stahl wrote this paper in 1989, the key justification for this assumption was that some shoppers actually enjoy shopping. Based on this intuition, the cost of search is effectively zero for them. We can expand upon this definition of zero search-cost consumers and consider, for example, those using the internet as zero search-cost consumers whereas those who are not using the internet as positive search-cost consumers.

In terms of collecting information, the internet has greatly reduced the cost of gathering information on just about anything including the price of various goods and services. There are price-comparison web sites such as Pricescan.com, Bizrate.com, Shoppers.com, etc where one can, at the click of a button, compare the prices of a specific item from many different sellers. Those with access to this information could then be accurately referred to as zero-search cost consumers. As enumerated in the empirical section, there are also other proxies that one can use to divide a population into those with positive search costs and those with zero or at least near-zero search costs.

This then helps me look at the price distribution that results due to the information asymmetry observable, as well as the prices paid by a zero search cost consumer as opposed to the prices paid by a positive search cost consumer.

While the model assumes that there are two pharmacies to begin with, the results can be extrapolated to show that they are true in a market with N pharmacies, without any loss in generality. It is assumed that the pharmacies are identical and selling a homogeneous product which is produced at a constant marginal costs. The model further shows that if all consumers have zero search costs then prices converge to marginal cost i.e. the Bertrand result, since all consumers will purchase from the lowest-priced store. Conversely, when all consumers have positive search costs, the price distribution converges to the monopoly price i.e. the Diamond result. Therefore, as figure 3.1 illustrates, the price distribution degenerates to monopoly prices when we have no zero search cost consumers, has positive mass when there is a mix of positive and zero search cost consumers, and then degenerates to marginal cost when all of the consumers have zero search costs.

Furthermore, the model shows that as the proportion of consumers with zero search costs goes from 0 to 1, the Nash Equilibrium price distribution changes continuously from the degenerate distribution at the monopoly price to the degenerate distribution at the competitive price.[11] An interesting prediction of this model is that as the number of pharmacies increases, the NE becomes more monopolistic. This is obviously contrary to expectations. The intuition is that in a market with a high proportion of positive search cost consumers, as the number of pharmacies in the market increases, the probability of being the lowest priced pharmacy decreases considerably. At

[11] This is stated in page 701 of the Stahl paper and the proof is presented in page 705.

this point, the expected payoff is higher for charging captive high search cost consumers high prices, than it is for attracting zero search cost consumers by charging low prices. Thus, pharmacies will carve out niche markets for themselves as long as there are some consumers who have zero search costs and some who have positive search costs. However, in a market with a sufficiently high proportion of zero search cost consumers, the competitive outcome will hold and we would expect prices to decrease as the number of stores increased.

Pharmacies serving the positive search cost consumers will charge higher prices since the positive search cost consumers are essentially captive. F(p) is the Nash Equilibrium cumulative probability distribution of prices charged by all the pharmacies. The Stahl model is a two-stage model, where sellers decide whether they want to cater to informed consumers or uninformed consumers in stage one. Based upon this decision, they pick the appropriate price for the good.

There are a large number of buyers and sellers in the market. Pharmacies have identical marginal costs of production which is assumed to be zero. While differing marginal costs have been shown to be sufficient to lead to price dispersion in the equilibrium (Reinganum, 1979), it is differing search costs that leads to price dispersion in the equilibrium in this model. The revenue function is R(p) = (p) D(p), where p is the price of the product, and D is the demand at that particular price. The revenue function is continuous, has a unique maximum and is strictly increasing for all prices below the price at which it is at the maximum. A certain proportion of the consumers, μ, have zero search costs while the rest ($1-\mu$) have a common, positive search cost, c.[12]

[12] This is shown in the Stahl paper on page 701.

Consumer Surplus

For consumers with positive search costs, it makes sense to search as long as the expected benefits from search are higher than the search cost. Therefore, for a consumer who observes the price z, the expected benefit of observing a lower price, p would be given by

$$CS\ (p; z) = \int_p^z D(x)dx \qquad (3.1)^{13}$$

The equation gives us the area under the demand curve between the prices of p and z. In other words, the expected benefit from search is computed via the increase in consumer surplus generated from the lower price located as a result of search.

We extrapolate this intuition to find the ex ante expected benefits given that there exists in the equilibrium a price distribution F(p).[14]

$$ECS\ (z) = \int_b^z CS\ (p; z)dF(p) \qquad (3.2)$$

Integrating by parts, we get

$$ECS\ (z) = [CS\ (p, z)F(p)]_b^z + \int_b^z D(p)F(p)d(p)$$

$$ECS\ (z) = \int_b^z D(p)F(p)d(p) + \ CS(z, z)F(z) - \ CS\ (b, z)F(b)$$

Since CS (z,z) = 0 by definition and F(b) = 0 because it is the lower bound of the cumulative distribution, we end up with

$$ECS\ (z) = \int_b^z D(p)F(p)d(p) \qquad (3.3)$$

[13] The equation numbers in this chapter are consistent with those in the Stahl paper without the chapter prefix i.e. equation 3.1 here is equation 1 in the Stahl paper.

[14] All the equations for expected consumer surplus are obtained from the Stahl paper from pages 702 and 709.

This equation gives us the expected value of gains from search by taking the difference between the original price observed and each lower price that exists in the equilibrium and multiplying it by the corresponding probability, in short, giving us the mean of the truncated distribution. Consumers should continue to search as long as ECS(z) > c. We can also state the optimal search rule at this juncture and it sums up as: continue searching if the observed price, z, is greater than the reservation price, r_F. Buy the good, if the observed price, z, is lower than the reservation price, r_F. Since ECS(z) is strictly increasing for all prices above the lower bound of the support, b for any price at which there is positive demand, we conclude that, if one exists, it is the unique solution for r_F,.

Pharmacy Price-Setting

Stahl's Lemma 1*: Given μ ϵ (0,1), if F(p;r) is an NE-distribution conditional on reservation price r, then it is atomless.*

Stahl presents no formal proof. The intuition lies in that if the distribution was atomistic, then undercutting prices by a small amount would lead to higher expected profits since the pharmacy will increase its share of shoppers. An atomless distribution overcomes this problem.

Stahl's Lemma 2: *If F(p; r) is an NE-distribution conditional on reservation price r, then P_r= min{r,ṕ}.*

This is fairly intuitive in presentation. No pharmacy will charge more than r, the reservation price, or ṕ, the monopoly price. Therefore, P_r, the upper bound of the support for F(p;r) will be the lower of the reservation price or the monopoly price.

The expected profit functions of the j^{th} pharmacy is as follows,[15]

$$E\,\pi_j\,(p_j, F) = \{\, \mu[1 - F(p_j; r)]^{N-1} + (1-\mu)/N \,\} * R(p_j) \qquad (3.4)$$

[15] From page 703 of the Stahl paper.

Where, $0 < \mu < 1$ and is the proportion of individuals with zero search costs, r is the unique consumer reservation price, and R(p) is the revenue function defined as R(p) = (p) D(p); D is demand for the good at price, p. The first part of the equation represents zero search cost consumers. $[1-F(p)]^{N-1}$ is the probability that all other pharmacies in the market are higher priced. Thus, if this is the lowest priced pharmacy, then it sells to all shoppers with zero search costs. The second part of the equation represents positive search cost consumers and they are equally divided up among the N pharmacies. When $\mu=0$, i.e., all consumers have positive search costs, the first part of equation (4) is zero whereas the second part reduces to $(1/N)R(p_j)$. Thus, since all pharmacies will get a fixed proportion of consumers, monopoly pricing will be the outcome. When $\mu=1$, i.e. all consumers have zero search costs, the second part of equation (4) is zero. In the first part of the equation, $[1-F(p)]^{N-1}$ also goes to zero since any pharmacy that charges higher than the lowest price in the market will not get any consumers at all. Thus, the expected profits for the pharmacy equals zero, which is the outcome with marginal cost pricing.

For the high price pharmacy:[16]

$$\pi = E\,\pi\,(P_r, F) = R(P_r) * (1 - \mu)/N$$

Thus, all the pharmacies (including the high-priced ones) will get an equal proportion of the positive search cost consumers. For Nash Equilibrium, the expected profits for both types of pharmacies have to be equal, otherwise pharmacies will have incentive to deviate. So setting the above two equations equal, and solving for F(p,r), we get,[17]

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[16] From page 703 of the Stahl paper.
[17] Equations 3.5 and 3.6 are from pages 703 and 704 of the Stahl paper.

$$F(p;r) = 1 - [\left(\frac{1-\mu}{N\mu}\right)(\frac{R(Pr)}{R(p)} - 1)]^{\frac{1}{N-1}} \qquad (3.5)$$

Taking the derivative of F(p;r) with respect to p gives us the density function f(p;r) as follows:

$$f(p;r) = \left(\frac{1-\mu}{N(N-1)\mu}\right)[\left(\frac{1-\mu}{N\mu}\right)\left(\frac{R(P_r)}{R(p)} - 1\right)]^{-\frac{N-2}{N-1}}[\left(\frac{R(P_r)}{R(p)}\right)\left(\frac{R'(p)}{R(p)}\right)] \qquad (3.\ 6)$$

which is non-negative for p ϵ [0, P_r] since $R(P_r) > R(p)$ for all p < ṕ.

Next, we want to solve for the lower bound for the support for F(p;r). We know that at lower bound the distribution degenerates to marginal cost, so F[b(r);r] = 0. Using this information and solving for (5), we get,[18]

$$R[b(r)] = \left[\frac{1-\mu}{1+(N-1)\mu}\right]R(P_r) \qquad (3.7)$$

Given this lower bound of the support for the price distribution, and the upper bound, which is defined as the minimum of the monopoly price or the reservation price, we can state that F(p;r) is a NE distribution of prices conditional on r. The following three facts demonstrate that.

(a) No pharmacy will charge higher than the reservation price, since it will fail to sell anything, or higher than the monopoly price, since that can never be optimal from a profit-maximizing standpoint.

(b) No pharmacy will charge less than b(r) since they would not gain any additional consumers i.e. they would still only sell to all the zero cost consumers and a fixed proportion of positive cost consumers. While b(r) is defined as the lower bound of

[18] Page 704 of the Stahl paper.

F(p;r), given the intuition presented here and in Lemma 1, it would equal the marginal cost.

(c) By construction of F(p;r) the profits for all pharmacies would be equal, so none have incentive to deviate.

3.2 Propositions

We explore the following two main propositions from the Stahl model:

1) In markets where all consumers have positive search costs, we get the Diamond result i.e. all pharmacies charge the monopoly price and in markets with all zero search cost consumers, we get the Bertrand result i.e. all pharmacies price at marginal cost. The Stahl model predicts that as the proportion of positive search cost consumers increases from zero up to a certain threshold, price dispersion will increase. Beyond that threshold, price dispersion will decrease. Price levels will, however, increase continuously as the proportion of positive search cost consumers go from zero to one.

2) In markets with a sufficient proportion of high search cost consumers, an increase in the number of pharmacies will result in an increase in prices to the point that the price distribution degenerates to the monopoly price. The intuition is that the only purpose in being the low priced pharmacy would be to capture all the zero search cost consumers, along with a fixed proportion of positive search cost consumers. As the number of pharmacies increases, the probability of being the low priced pharmacy decreases exponentially and therefore there is greater incentive in charging a high price.[19] Conversely, in markets with a proportion of zero search cost consumers above a certain threshold, we expect the competitive

[19] This result is presented in proposition 4 on page 706 of the Stahl paper.

market outcome i.e. price levels will decline with an increase in the number of stores.

3.3 Comparative Statics

Table 3.1 summarizes the comparative statics discussed next. E(p) is the expected price level, F is the cumulative price distribution, μ is the proportion of consumers with zero search costs and N is the number of pharmacies in the market. For the comparative statics shown in Table 3.1, for the case of the number of pharmacies increasing leading to an increase in the price levels, we assume that the proportion of zero search cost consumers is below a certain threshold. Conversely, if the proportion of zero search cost consumers is above a certain threshold, an increase in the number of pharmacies will lead to a decrease in price levels i.e. the competitive outcome.

Therefore,

$$\frac{\delta E(p)}{\delta \mu} < 0, \text{ and}$$

$$\partial E(p)/\partial N < 0 \text{ for } \mu > \mu^*$$
$$\partial E(p)/\partial N > 0 \text{ for } \mu < \mu^*$$

We see that, holding all other things constant, as the proportion of consumers with zero search costs increases in a market, the expected price levels decline. We also see that, once again holding all other things constant, as the number of pharmacies in a market increases, the expected price levels increase.

$$\frac{\delta F(p)}{\delta \mu} \begin{cases} > 0, if\ \mu < \mu' \\ < 0, if\ \mu > \mu' \end{cases}$$

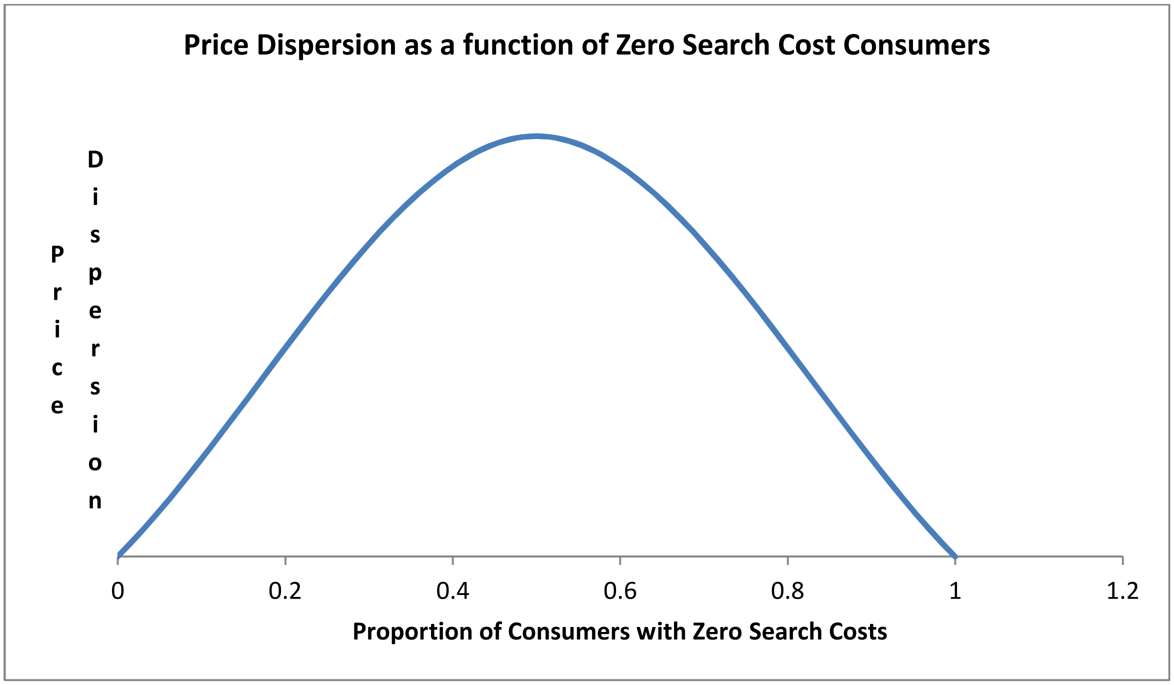
$$\frac{\delta F(p)}{\delta N} \begin{cases} > 0, if\ N < N' \\ < 0, if\ N > N' \end{cases}$$

where μ’ and N’ are threshold values for the respective parameters above which the price distribution converges, to the competitive market outcome in the case of the proportion of zero search cost consumers, and to the monopoly outcome in the case of the number of pharmacies in the market with a high proportion of high search cost consumers, and to the competitive outcome in the case of the number of pharmacies in the market with a high proportion of zero search cost consumers, respectively.

Table 3.1 Comparative Statics

	E(p)	**F(p;r)**
μ↑	↓	Initially ↑, then ↓
N ↑ (for $\mu > \mu^*$)	↓	Initially ↑, then ↓
N ↑ (for $\mu < \mu^*$)	↑	Initially ↑, then ↓

Figure 3.1: Price dispersion and Zero Search Cost Consumers



4. Data

4.1 Brick and Mortar and Online/Mail-Order

The brick and mortar data set is from the Maryland State Attorney General's (SAG) web site, which posts the prices of the twenty six most popular drugs in the state Medicaid program. Every pharmacy in Maryland that was reimbursed through Medicaid reports the cash price for the drug, i.e. the price that a consumer paying out-of-pocket would pay. Along with these prices, I was also able to obtain the addresses of each pharmacy that posted the prices of the drugs from the same source. I look at 970 pharmacies located in 160 towns in the state of Maryland, and specifically look at how competition within the township affects pricing strategies. I also collected data on various characteristics of the twenty six drugs from a number of sources including the FDA web-site.

Prices of the same twenty six drugs were also collected in December 2009 from a total of thirteen online and mail-order companies. These data were merged with the Maryland data described above. Since the two sets of prices were collected about a year apart, I do not do any direct price level comparisons. I do, however, look at relative prices and price dispersion.

The broad scope of the data – twenty six different products in the prescription drugs category across 165 markets with distinctions made between online and brick and mortar channels - gives me the ability to test my hypotheses with considerable confidence. The data for the brick and mortar pharmacies[20] were obtained in January

[20] I collected data from 13 online and mail-order pharmacies for the prices of the same 26 prescription drugs. These data were collected from BidRx for the mail-order pharmacy prices and from Drugstore.com, Familymeds.com and Costco Online. All of these pharmacies are accredited by the National Association of Pharmacy Boards.

2009 from the SAG web-site and the data are for prices from June of 2008, i.e. the State Attorney General's office posted prices with a lag of about six months. The prices are from nine hundred and seventy pharmacies statewide. The data were collected when the pharmacies submitted paperwork for Medicaid payments for prescriptions filled. If a pharmacy did not fill a prescription for an individual on Medicaid for a specific drug in the period in which the data were collected, then the price of that drug from that pharmacy is not included in the data set. The prices listed were the posted retail prices by the pharmacies (one that an out-of-pocket consumer would pay) and not the amount that was reimbursed to the pharmacy by Medicaid. According to the SAG's web-site, the purpose of the web-site was to make prices of prescription drugs more transparent for consumers, particularly those who were paying out-of-pocket. Thus, the prices listed are the actual retail price that the pharmacy would charge a consumer who was paying cash for the pharmaceutical drug.

The SAG's website also has a database that listed all the pharmacies in the state. There are exactly one thousand and twenty pharmacies listed in this database. Upon further research, I found that thirteen of the pharmacies had shut down. It is unknown why the remaining thirty seven did not fill any prescriptions for Medicaid. It is possible that they did not carry these specific drugs or that they did not cater to a Medicaid patient in that time period. Furthermore, in the process of cleaning the data, I found that there were a number of stores that had changed names, including a couple of chains that had been acquired by CVS.[21] The cleaned data set reflects those changes.

[21] CVS went on a big acquisition spree over the last few years. Although they had acquired Revco in 1997, a lot of the pharmacies continued operating under the Revco name. They also merged with Caremark in 2006.

The pharmacy industry can be sub-categorized in three different groups - big chains, small, independent pharmacies, and supermarket pharmacies such as Target, Walmart, etc. The big chains and the supermarket pharmacies negotiate wholesale prices with the manufacturers individually while the small, independent pharmacies are able to form coalitions that give them greater negotiating power than they would have if they were to negotiate individually. A thorough inspection of the data was necessary to identify stores by whether they were part of a chain as opposed to independently owned. Furthermore, this task was made more difficult as most stores did not have a singular system in reporting their names. Neighborcare pharmacies, for instance, reported its name as “Neighborcare,” “NEIGHBORCARE” and “Neighborcare Pharmacy,” so it was necessary to change them to a uniform format. For a lot of names that reflected some heterogeneity, it was necessary to go to the corporate web-site and track down each store by location to ensure that they were indeed part of the same chain. However, it was not deemed necessary to ascertain this information in all cases. For instance, I was able to determine from my own knowledge base that Walmart, Wal-mart and WALMART were in fact all part of Walmart.

Furthermore, there is some ambiguity in terms of how a pharmacy company may identify itself and what category it actually falls into. The Medicine Shoppe International Inc, for instance, considers itself as an independent pharmacy group and since it is based on the franchise model, as opposed to corporate ownership, it is true via that definition. However, as they have over 850 locations in the U.S. and over 400 more internationally, they might also be considered a chain and in 1998 were, in fact, named the Pharmacy Chain of the Year by Drug Topics magazine. The Medicine Shop has 27 locations in

Maryland, and I categorize it as a chain store for my analysis. For all pharmacies with more than one location in the state, I individually scrutinized the pharmacy to categorize it as either an independent pharmacy or part of a chain. Two hundred and twenty six out of the two hundred and fifty two unique pharmacy names in Maryland have only one location. All this work in identifying pharmacies by chain or independent ownership might seem a bit unnecessary at first glance. However, bear in mind that I am interested in price dispersion in the retail prescription drug market and I am looking at individual geographic markets by township for my empirical analysis. I consider it highly likely, particularly after a cursory glance at the data, that some of these pharmacies have uniform pricing policies, at least at the state level. I saw consistencies in the pricing across a specific drug across a specific chain when cleaning the data. For example, Flonase is sold at ninety nine Rite-Aids for a total of fifteen different prices across Maryland. Two of these fifteen prices appear roughly half the time. Therefore, a pricing policy that perhaps addresses the characteristics of a market at the state or even national level will not reflect the idiosyncrasies of a market at a much more local level. In short, company-wide pricing policies will work against the predictions of the theoretical model given that we are defining markets at a more granular level.

Although I am interested in the nature of prices and price dispersion due to consumer heterogeneity, I considered it necessary to collect drug-specific information as well to avoid omitted variable bias in my empirical analysis. It is unlikely that consumers will change search behavior because a drug is a new molecular entity implying that a new active ingredient was used in this drug to treat this illness/condition. However, it is entirely possible that manufacturers have a different pricing strategy for this type of drug and it follows that the prices observed at the retail level reflect prices set at the manufacturer level.

A number of pharmaceutical drugs are reformulations of existing drugs either with an additional compound or through changing the ratios of existing compounds for “cocktail drugs.” For instance, Prilosec, a gastrointestinal agent, added Magnesium to Omeprazole to make their existing formulation more effective in combating chronic heartburn. Reformulations of this type are commonplace and also allow the drug-maker to extend their existing patent.

Information on each of the drugs was collected from the FDA web site and cross-checked with information from drugstore.com and drugs.com – an excellent and credible resource for any questions on any prescription drug. This information was then further cross-checked with The Physician’s Desk Reference (PDR 63rd Edition) (2009).

Data were collected on whether the drug was a brand name drug or a generic, whether it had therapeutic equivalents, the drug class as well as the symptom/illness it was used for, whether the drug was a new molecular entity or a new salt/ether entity, and whether the review classification for the drug by the FDA was standard or priority. A drug with a priority classification by the FDA is considered to be, potentially, highly beneficial from a societal point in that it shows significant promise to treat, prevent, or diagnose a specific condition or illness. As a result, considerable resources are devoted by the FDA to approve this drug in the fastest time possible. Drugs with this special status, once approved, could reflect considerably different pricing patterns than drugs with a standard review classification.

A good deal of effort went into classifying each of these drugs by the demographic group that consumes them as well as whether they are used on an ongoing basis or if they are a one-time use only pharmaceutical. For instance, Lipitor is used on an ongoing basis since it is consumed for the purposes of lowering or maintaining a specific level of blood cholesterol. Consumers are more likely to be familiar with the price distribution as they shop around for repeat purchases than they would be if it was a one shot deal. Concerta, on the other hand, is a Central Nervous System stimulant and used to treat Attention Deficit Hyperactive Disorder (ADHD). It is of a highly addictive nature and according to the PDR guide capable of causing "severe mental changes." Given these characteristics, it is unlikely that Concerta would be prescribed for an extended period. Similarly, a great deal of care was put into deciphering whether or not the use of a pharmaceutical could be narrowed down to a specific demographic group. All the drugs fell into one of five groups for the demographic variable: (1) general; (2) men; (3) women; (4) young; and (5) elderly. Flonase, for example, is used to treat allergies and is used by all groups and therefore falls into the general category. Ortho-Evra is a birth control drug making it easy to assign to women. Celebrex, however, is a Non Steroidal Anti-Inflammatory (NSAID) used to treat pain and inflammation. Upon closer inspection, I found that it is typically prescribed to treat Osteoarthritis. Thus, it is *more likely* that Celebrex is used by the elderly as opposed to any of the other listed demographic groups. All twenty six of the drugs were thoroughly researched for clarification purposes.[22]

I split the pharmacies by individual municipalities in the state of Maryland. The purpose was to break the state up into individual geographic markets where consumers

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[22] Professor Karen Blumenschein's assistance in working through this aspect of the data was invaluable and I am indebted to her for helping with this work.

might price shop and purchase their prescription needs. However, Baltimore has 175 pharmacies located in the Metropolitan Statistical Area and it seems unlikely that consumers would travel across a city so large to price shop for pharmaceuticals. I split the MSA up into five distinct districts[23] – Baltimore downtown, Baltimore East, Baltimore North, Baltimore South and Baltimore West. We then matched the zip codes of each individual pharmacy to the zip codes within these five districts by using a map provided by the Maryland Department of Planning. I felt that this step would better reflect economic markets, provide a better test of my hypothesis and reconcile the theory with the empirical analysis.[24]

Prices of the same twenty six drugs were also collected in December 2009 from a total of thirteen online and mail-order companies. These data were merged with the Maryland data described above. Since the two sets of prices were collected about a year apart, I do not do any direct price level comparisons. I do, however, look at relative prices and price dispersion. Table 4.1 lists each of the drugs in this data set along with the number of observations of each drug and the illness or symptom the drug is used to treat.

In the Maryland data set, all the package sizes for any specific drug were the same, i.e. the price quoted from every pharmacy in Maryland for Adderall XR 20 mg is for a quantity of 30 capsules. All the drugs were for a one month supply. However, I adjust for a per unit (per pill) price in anticipation of the desire to compare absolute measures across the two data sets.

[23] This was based on how various businesses including the Baltimore Restaurant Association splits the city into five business regions based on geography.
[24] However, I acknowledge that I do not have a perfect delineation of markets. While I consider each municipality a market, there will instances where the municipalities are adjoining and any delineation will be arbitrary.

One of the measures I use to analyze price levels is markup over minimum price in a given market.[25] This is the measure I use to compare online price mark-ups to offline price-markups. By markup, I mean that I am measuring the percentage that customers pay over the minimum price that they could pay for that particular drug. Thus, if the lowest price observed in the marker for a specific drug is \$10 and consumers are paying \$15 on an average, then they are paying 50% over the lowest price they *could* pay for the drug. So, it is in effect the proportion above the lowest price that is being charged by various retailers. I think that this is an appropriate variable since the minimum price charged could serve as a proxy for the marginal cost of the product. I realize that this measure is sensitive to outliers. However, I have a total of 14,783 price observations and 2,151 minimum prices for the i^{th} drug in the k^{th} town.[26] For price dispersion, I use range and coefficient of variation, which are the standard measures used in price dispersion literature.

Therefore,

$$\text{Price Markup}_{\text{ijk}} = \frac{(\text{Price Quoted}_{\text{ijk}} - \text{Minimum Price}_{\text{ik}})}{\text{Minimum Price}_{\text{ik}}},$$

where i is the i^{th} drug, j is the j^{th} store and k is the k^{th} market.

Thus, I looked at the difference between the price quoted and the minimum price and normalized this difference by the minimum price of that pharmaceutical. This makes for a more valid comparison across drugs. Figure 4.1 shows a plot of markup over minimum price by individual drugs. It can be seen that drugs like Adderall XR and Advair Diskus are competitively priced with a high density of observations close to the

[25] Markets are defined as 160 individual municipalities in Maryland along with the city of Baltimore, which is divided into five individual markets as explained earlier in this chapter.
[26] There are 14,487 observations from brick and mortar pharmacies. I also collected 296 observations on the same 26 drugs from online pharmacies for a total of 14,783 observations.

minimum price. As shown in Table 4.2, the range for Adderall XR, for example, extends from a minimum of $3.73 to a maximum of $7.87 with a mean of $5.67 and a coefficient of variation of 0.133. In contrast, when I look at Ortho Evra, I observe a much wider range in the observations. The range for Ortho Evra extends from $11.67 to $119.30 with the mean at $19.49 and a coefficient of variation of 0.313. (The second highest price for Ortho Evra at a different pharmacy in a different town was $115.30). The average of the markup over the minimum price by each town and as defined above for the entire set of 14,783 observations on all drugs is an astounding 34.43%. In other words, one could walk in to a pharmacy at random and expect to pay 34.43% above what one would pay for that specific drug in that specific town if one were informed and purchased it from the lowest cost seller.

Figure 4.1shows density plots for each of the drugs by markup over the minimum price. This particular measure gives us the advantage of scaling the drug prices to the same level i.e. proportion by which the observed price is above the minimum price of that specific drug. We also looked at the density plots for the natural logarithm of the unit prices. These plots were practically identical to the ones presented for the markup with the major difference being that the scale was different.[27]

4.2 Summary Statistics and Overview of the Data

I present several tables to illustrate the distribution of drug prices. Table 4.2 and Table 4.3 present the summary statistics for each individual drug. In Table 4.2, I present the mean, the standard deviation, the minimum, the maximum, the ratio of the maximum to the minimum, and the coefficient of variation of price per unit. The price per unit was

[27] I do not include these plots in the appendix since they do not add very much information, however, they are available upon request.

computed as price per tablet or as in the case of Ortho Evra, the price per patch. Since all the prices for each specific drug were for the same package size, my results would not be any different if I were to look at the total price as opposed to the unit price other than a scalar change for absolute measures. The prescription drug package sizes were all for a typical one month supply. While we use all the other statistics shown in Table 4.2 for inferential work presented later, the purpose of the Max/Min ratio is just to serve as a descriptive measure with the sole purpose of emphasizing the marked differences in prices observed.

Table 4.3 presents observations at the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentile as well as the third and the fourth moments about the mean, the skewness and kurtosis, respectively. I also present the ratios for the 10^{th} and the 90^{th} percentile and found that the average across all drugs was 1.4. In other words, even after dropping the 10 percent of the most extreme observations on both tails of the distribution, the maximum (90^{th} percentile) price was still, on an average, 40 percent above the minimum (10^{th} percentile) price. The skewness measure gives us an idea of the symmetric (or asymmetric) nature of the distribution. The distribution of prices for Adderall XR, for instance, with skewness of 0.13 is pretty close to normal whereas Lexapro with a skewness of 6.642 is skewed heavily to the right. A value of zero indicates a symmetric distribution whereas positive or negative values indicate right and left skewness respectively.

The kurtosis measure tells us how flat or peaked the distributions are and for a normal distribution we should have a value of 3. Heavy tailed or peaked distributions will have kurtosis above 3 whereas light tailed or flat distributions have a value of less than 3 for kurtosis. Once again, Adderall XR has a value of 3.061 whereas Ortho Evra has a value of 206.867, indicating observations with significant deviations from the center of the distribution. For the purposes of later empirical analysis, I am not worried about normality since my sample size is over fourteen thousand values in prices and over two thousand values in summary statistics.

Table 4.4 lists and describes the variables I use in my analysis. The two dependent variables I use are *LN(price)* the natural log of price of prescription drugs to measure price levels, while *Variation*, the coefficient of variation of drug prices, is used to measure dispersion in the price distribution. I also use *Minimum Wholesale Price*, which is the minimum average wholesale price of drugs, *Minimum Price*, which is the minimum price of the i^{th} drug in the k^{th} town, and *Mean Price*, which is the average price of the i^{th} drug in the k^{th} town, as a control of the price level of the drug itself. As discussed earlier, I want to control for the propensity to search, which may be higher for drugs that are higher prices, as opposed to drugs that are lower priced. There are also a number of other independent variables described in the table and discussed in length in chapter 5, as well as chapter 6.

Table 4.1: List of prescription drugs along with symptoms/illnesses the drugs are used to treat

N	**Name and Dosage of Pharmaceutical**	**Treatment**
543	Adderall XR 20mg	ADHD
656	Advair Discus 250-50mcg disk	Asthma and chronic lung disease
654	Albuterol 90mcg	Asthma, emphesyma, chronic bronchitis
397	Celebrex 200mg	Pain and inflammation
634	Combivent 103-18mcg	Asthma, emphesyma, chronic bronchitis
612	Concerta 36mg	ADHD
434	Depakote 500mg	Seizures, migraine headaches, manic episodes
759	Flonase 50mcg	Allergies
733	Fosamax 70mg	Osteoporosis
353	Furosemide 40mg	High blood pressure, congestive heart failure
722	Lexapro 10mg	Depression and anxiety disorder
813	Lipitor 10mg	Control cholestrol
276	Lotrel 10-20mg	Blood pressure
382	Nexium 40mg	Gastroesophageal reflux disease (GERD)
674	Norvasc 10mg	High blood pressure
658	Ortho Evra 20-150/24h	Birth control
457	Plavix 75mg	Reduce risk of stroke or heart attack
576	Pravachol 40mg	Control cholestrol
844	Prevacid 30mg	Ulcers and GERD
459	Risperdal 1mg	Emotional and mood disorders
523	Seroquel 100mg	Schizophrenia and bipolar disorder
487	Singulair 10mg	Treatment of asthma
557	Toprol XL 50mg	High blood pressure and congestive heart failure
544	Wellbutrin XL 300mg	Depression and seasonal affective disorder
361	Zetia 10mg	Lowers cholestrol
675	Zoloft 100mg	Depression, panic disorder, OCD, PTSD

Source: Drugs.com, FDA website and PDR 63rd edition.

Table 4.2: Summary statistics of the Maryland Drug Price data set

	Obs	Mean	Std.Dev.	Min	Max	Max/Min	CV
Adderall XR 20mg	543	5.675	0.757	3.733	7.866	2.107	0.133
Advair Discus 250-50mcg	656	3.671	0.407	2.515	6.628	2.636	0.111
Albuterol 90mcg	654	1.562	0.325	0.362	3.409	9.407	0.208
Celebrex 200mg	397	2.203	0.587	1.425	4.171	2.927	0.266
Combivent 103-18mcg	634	7.588	1.423	3.974	21.673	5.454	0.188
Concerta 36mg	612	5.196	0.626	3.189	6.833	2.142	0.120
Depakote 500mg	428	3.512	0.614	1.973	6.680	3.385	0.175
Flonase 50mcg	753	6.230	0.794	3.743	10.979	2.934	0.127
Fosamax 70mg	727	22.754	2.726	16.680	47.615	2.855	0.120
Furosemide 40mg	353	0.322	0.072	0.130	0.580	4.473	0.224
Lexapro 10mg	722	3.459	0.428	2.466	10.609	4.303	0.124
Lipitor 10mg	813	3.150	0.386	2.256	6.648	2.946	0.123
Lotrel 10-20mg	276	3.773	0.397	2.845	5.466	1.921	0.105
Nexium 40mg	382	5.742	0.609	4.128	7.428	1.799	0.106
Norvasc 10mg	668	2.614	0.248	1.975	5.196	2.631	0.095
Ortho Evra 20-150/24h	658	19.494	6.108	11.667	119.300	10.226	0.313
Plavix 75mg	457	5.059	0.763	3.979	15.045	3.781	0.151
Pravachol 40mg	570	5.392	0.538	4.036	8.400	2.081	0.100
Prevacid 30mg	844	5.939	0.695	4.002	10.883	2.720	0.117
Risperdal 1mg	459	5.477	0.623	3.932	9.115	2.318	0.114
Seroquel 100mg	523	4.780	0.536	3.200	7.582	2.369	0.112
Singulair 10mg	487	4.129	0.522	2.911	11.662	4.007	0.126
Toprol XL 50mg	557	1.223	0.162	0.785	2.179	2.775	0.132
Wellbutrin XL 300mg	538	5.711	0.742	3.657	9.990	2.732	0.130
Zetia 10mg	361	3.250	0.392	2.472	5.508	2.228	0.121
Zoloft 100mg	669	3.358	0.335	2.418	6.312	2.610	0.100

Table 4.3: Percentile distribution of unit prices in the Maryland Drugs data set

	p10	*p25*	*p50*	*p75*	*p90*	*skewness*	*kurtosis*
Adderall XR 20mg	4.608	5.262	5.800	6.100	6.739	0.130	3.061
Advair Discus 250-50mcg	3.166	3.391	3.661	4.006	4.150	0.535	6.567
Albuterol 90mcg	1.164	1.440	1.626	1.705	1.941	0.383	7.309
Celebrex 200mg	1.654	1.815	2.033	2.383	3.217	1.494	4.663
Combivent 103-18mcg	6.102	6.524	7.271	8.412	9.222	2.684	23.311
Concerta 36mg	4.503	4.864	5.197	5.500	6.066	0.632	4.051
Depakote 500mg	2.630	3.012	3.646	4.000	4.217	-0.428	4.056
Flonase 50mcg	5.264	5.674	6.156	6.749	7.437	-1.116	10.601
Fosamax 70mg	19.460	20.743	22.663	24.398	25.998	-1.115	18.243
Furosemide 40mg	0.237	0.300	0.330	0.366	0.366	-0.277	5.365
Lexapro 10mg	3.050	3.233	3.466	3.632	3.866	6.642	111.594
Lipitor 10mg	2.739	2.871	3.066	3.433	3.633	1.740	15.884
Lotrel 10-20mg	3.338	3.510	3.690	4.000	4.366	0.844	3.734
Nexium 40mg	4.916	5.319	5.766	6.166	6.600	-0.139	2.534
Norvasc 10mg	2.291	2.462	2.556	2.800	2.859	-2.076	28.369
Ortho Evra 20-150/24h	16.030	17.663	19.197	20.663	21.597	13.134	206.867
Plavix 75mg	4.381	4.663	5.000	5.366	5.698	5.994	71.829
Pravachol 40mg	4.800	5.000	5.276	5.782	6.133	-2.484	20.812
Prevacid 30mg	5.063	5.450	6.000	6.443	6.833	0.560	5.702
Risperdal 1mg	4.616	5.066	5.423	5.866	6.400	0.180	4.601
Seroquel 100mg	3.962	4.454	4.766	5.233	5.433	-0.246	3.882
Singulair 10mg	3.566	3.816	4.177	4.433	4.600	5.937	90.311
Toprol XL 50mg	1.023	1.107	1.202	1.333	1.466	0.359	4.429
Wellbutrin XL 300mg	4.833	5.218	5.666	6.266	6.428	0.024	8.399
Zetia 10mg	2.698	2.988	3.172	3.533	3.696	1.057	6.426
Zoloft 100mg	2.895	3.157	3.300	3.633	3.712	-2.126	22.836

Table 4.4: Description of variables included in analysis.

Average Wholesale Minimum Price	Minimum average wholesale price for the drug
Average Markup	the average of the markup (as defined in section 5.2) for the i^{th} drug in the o^{th} market.
Brand Name Dummy	1 if drug is a brand name and 0 if generic
Chain Store Dummy	1 if store is part of *any* chain; 0 if independent
Pharmacy Medicaid	a relative measure of the percent of consumers at a pharmacy on Medicaid
Coefficient of Variation	the coefficient of variation in the prices of the i^{th} drug in the k^{th} town
LN(price)	The natural log of price
Mean Price	The average price of the $i^{ith\ drug}$ in the k^{th} town
Minimum Price	the minimum price of the i^{th} drug in the k^{th} town
Online Pharmacy Dummy	1 if sold by an online pharmacy; 0 if it's a brick and mortar pharmacy
Number of Pharmacies	Number of Pharmacies in town that sold that drug to folks on Medicaid
Pharmacy Chain Dummy	1 if price from a pharmacy chain, 0 if from an independent pharmacy
*Number of Pharmacies * Search Cost*	interaction term that captures whether the impact of a higher proportion of positive search cost consumers causes price levels for the i^{th} drug at the j^{th} pharmacy to increase as the number of stores in the market increases
Town Medicaid	a relative measure of the percent of consumers in a town on Medicaid
Unit Price	Unit price of prescription drugs
Value of Search	equal to the difference between the expected price and the minimum price of the drug normalized by the minimum price in that market

Figure 4.1: Mark Up over the Lowest Price of Each Prescription Drug

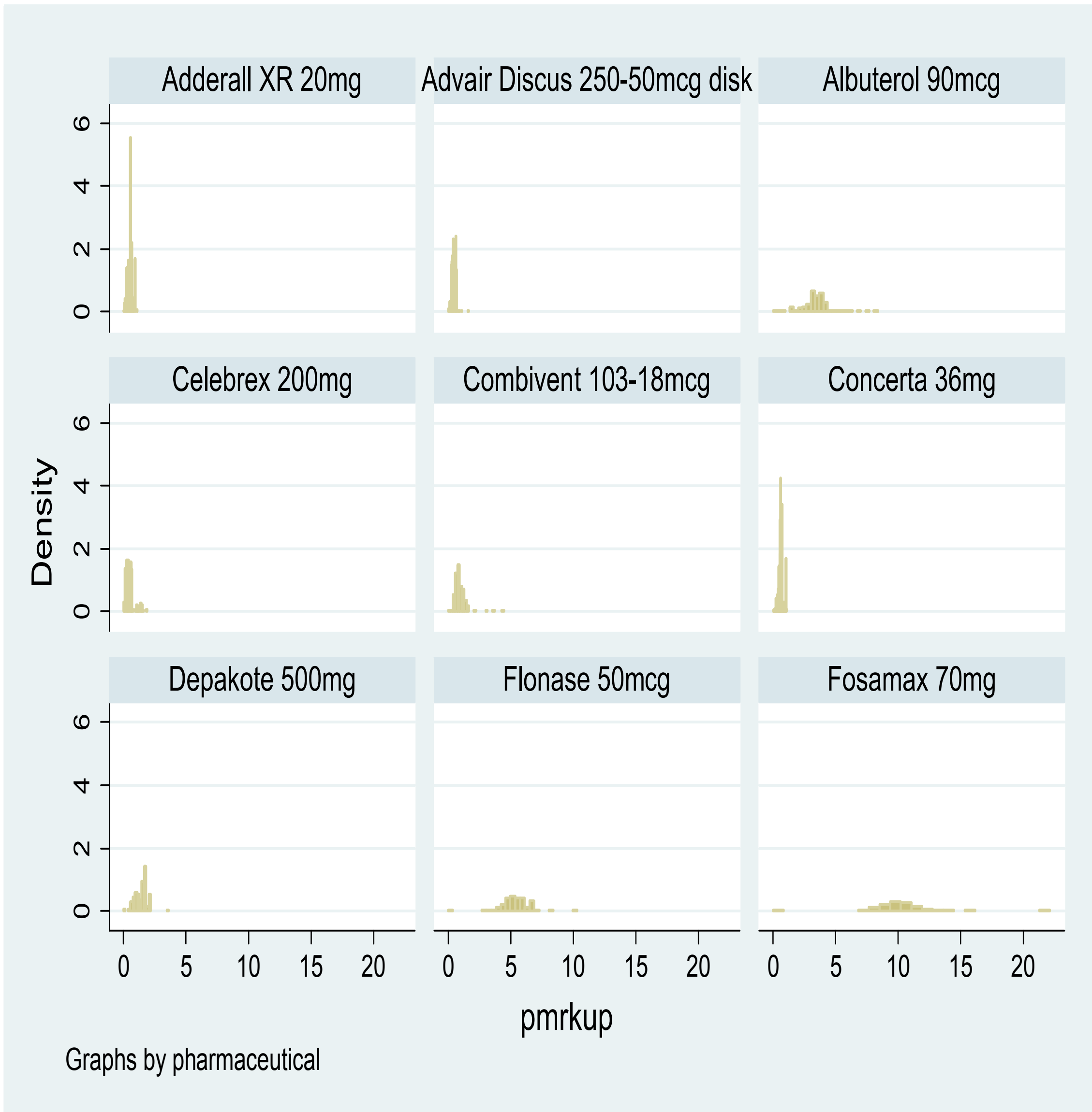


Figure 4.1(continued): Mark Up over the Lowest Price of Each Prescription Drug

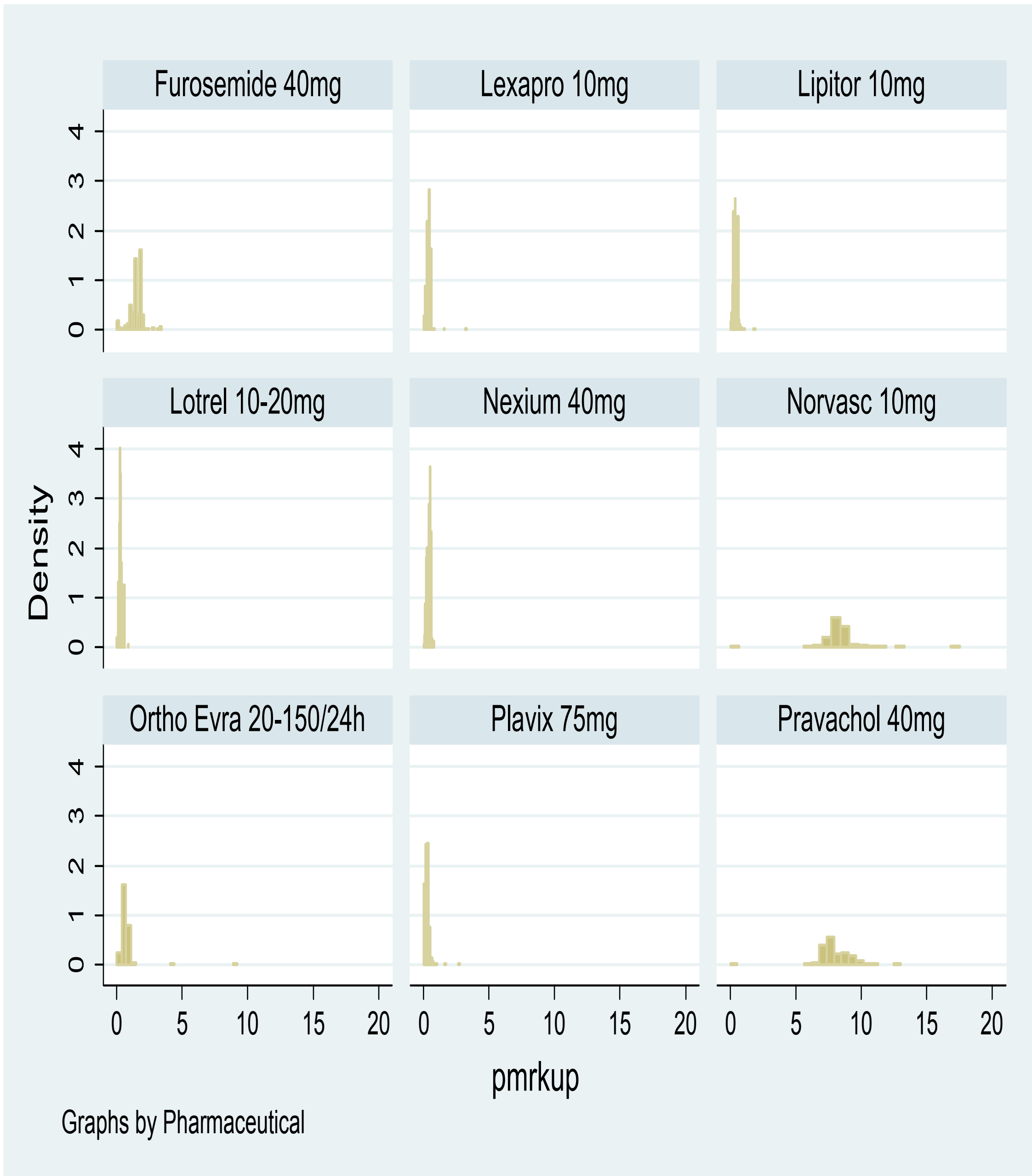
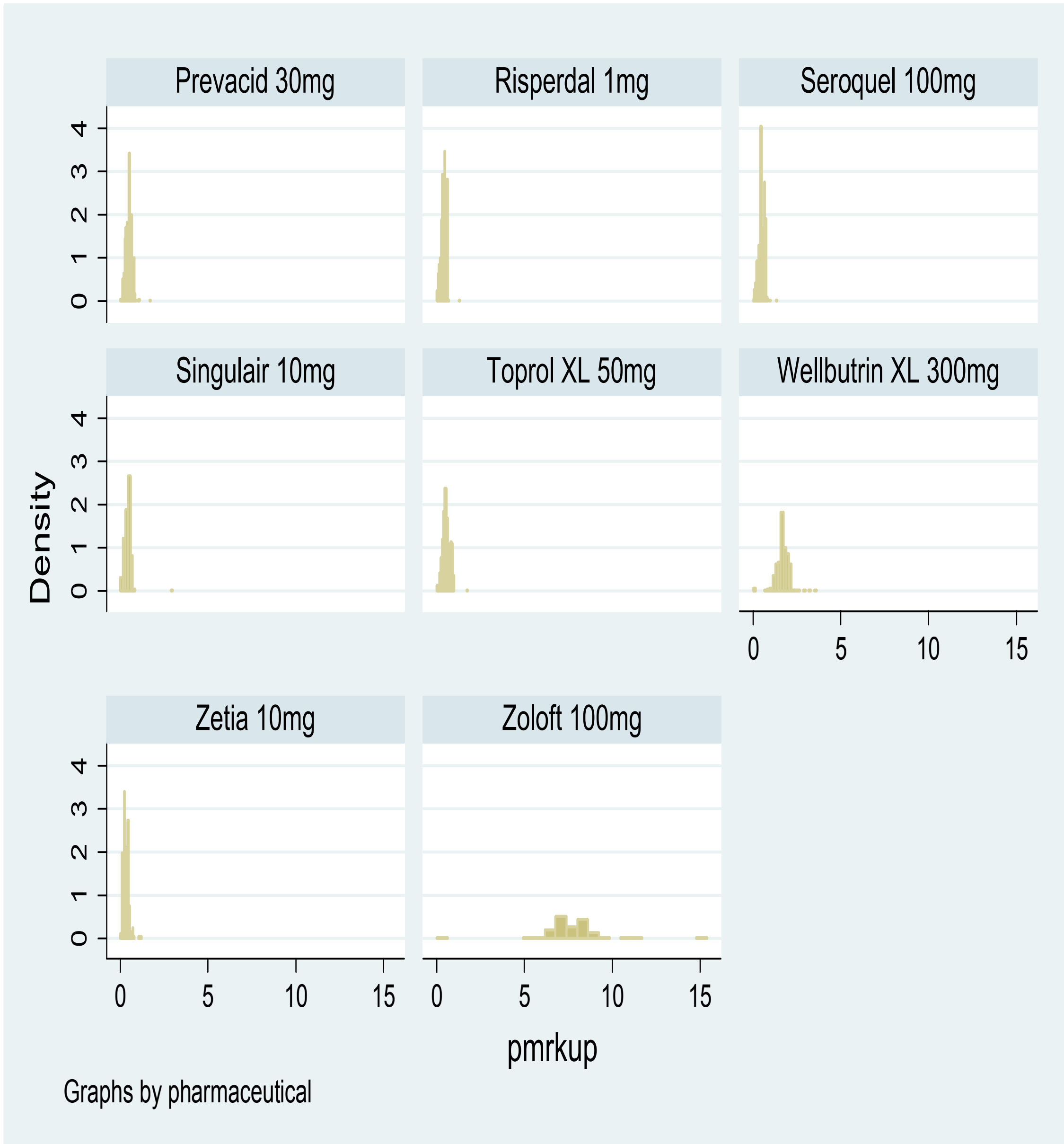


Figure 4.1(continued): Mark Up over the Lowest Price of Each Prescription Drug



5. Empirical Model and Econometric Issues

For most of my analysis I employ a drug fixed-effect model since the focus of this dissertation is to explain the effect of various market characteristics on observed price levels as well as price dispersion. I use the number of pharmacies in the market as a measure of market concentration and various measures of search cost defined below. Since the Stahl model predicts that price distribution is a non-monotonic function of each of these two parameters, I included quadratic terms for both in my regression specifications. I also include an interaction term between the proportion of positive search cost consumers and the number of pharmacies in the market. The intuition for including this interaction term is that the effect of the proportion of positive search cost consumers on price dispersion may vary as the number of pharmacies in the market changes.

5.1 Search Cost Measures

I propose the following ways to identify low (zero or near zero) search cost individuals and differentiate them from high search cost individuals.

a) *Pharmacy Medicaid and Town Medicaid*: I identify pharmacies serving a relatively higher proportion of low-income groups, as well as towns with a higher proportion of low income individuals. Contrary to markets for other goods, low income consumers of prescription drugs are typically the high search cost consumers. The intuition is as follows - in other markets, search cost incorporates the opportunity cost of the time of an individual. Therefore higher income individuals have a higher search cost. For prescription drugs (or most healthcare related services), a greater proportion of high income individuals have health insurance coverage relative to low income individuals.[28] As a result, low income individuals are more likely to pay cash prices for prescription drugs, the same prices that we are analyzing, as opposed to high income individuals. I do not know of any other work that has presented this intuition and conducted a formal analysis of it.

b) *Online versus Brick and Mortar*: Online consumers have lower search costs relative to offline consumers. It is significantly less costly to search for prices online than it is for brick and mortar stores. I am not aware of any formal studies of the online prescription drug market in spite of the existence of numerous online pharmacies. As established in the pricing literature, the prices offered by online sellers reflects competition among them for consumers, all of whom have relatively low search costs compared to offline consumers.

5.2 Price Levels

As discussed earlier, to measure the impact of various search cost measures as well as market level characteristics on price levels, I use the natural log of price. However, when I compare across online and offline markets, given that I obtained the two sets of data about a year apart, I use price mark-up as the measure of price levels. The price markup is defined as the difference between the observed price for the i^{th} drug at the j^{th} pharmacy in the k^{th} market and the minimum price for the i^{th} drug in the k^{th} market, normalized by the minimum price as well. This measure negates the impact of

[28] According to surveys by the Center for Studying Health System Change, in 2007, 27.1% of low income nonelderly individuals did not have any health insurance coverage as opposed to 11.9% and 5% for middle and high income individuals, respectively.

any temporal changes in prices since I consider online and offline markets separately in computing this measure.

$$\text{Markup}_{\text{ijk}} = \frac{(\text{Price Quoted}_{\text{ijk}} - \text{Minimum Price}_{\text{ik}})}{\text{Minimum Price}_{\text{ik}}}$$

The predictions from search models in general and Stahl's model in particular are that, holding all other things constant, greater search will lead to lower price levels.[29] Additionally, while search cost itself is independent of price, the *propensity* to search is not, i.e. if one spends a whole day searching, then in terms of opportunity cost, one will incur equal costs in searching for a book or a house. However, we are more likely to actually undertake search before buying a house than we are before buying a book. Furthermore, Stahl's model predicts that with a sufficiently high proportion of positive search cost consumers, as the number of firms increases, price levels will increase. This is completely counter to expectations based on traditional microeconomic theory, where the key driving force for a competitive outcome is based on the assumption of perfect information.

5.3 Price Dispersion

I use the coefficient of variation in prices as the dependent variable to measure dispersion in prices. This is the appropriate measure to use since I am testing hypotheses on whether the price distribution is expanding or contracting. Furthermore, this relative measure of dispersion better preserves the integrity of the work over absolute measures. Measures such as the range or the standard deviation are more likely to show spurious correlation with the independent variables. I look at the CV for each drug in each town

[29] I recognize that there is an endogeneity problem since higher price levels increase the propensity to search. However, I address the issue by including fixed effects for each drug, which should in theory absorb drug-specific (i.e. price-level specific) search behavior.

since each town constitutes an individual market in my framework. Recall that there are 14,783 individual price observations in the Maryland data set for pharmaceutical prices (combined with the online/mail-order pharmacies). I compute the coefficient of variation for the j^{th} drug in the i^{th} town for each of the 26 drugs in the 165 markets: 160 towns (with Baltimore City split up into five regions) and 13 internet/mail-order pharmacies, which are defined as the one online market. Each of these markets has between 1 and 50 pharmacies located within the market and I measured the dispersion in the prices of a specific drug across pharmacies within individual markets. Therefore, I should have 4,290 observations of dispersion (26 drugs multiplied by 165 markets) but because certain drug prices are not observed at any of the pharmacies in some markets, we actually have 3,439 observations on dispersion. A further 1,279 observations were dropped because the drug price was available from only one pharmacy in that specific market. In such cases, the observed dispersion of zero was due to not observing a second price, as opposed to the fact that the prices were equal. Out of the remaining 2,160 observations, there are a total of 9 observations of CV with a value of zero in instances where at least two pharmacies (and in some cases, as many as 12 pharmacies) offered a prescription in a specific market. For the number of stores in town, I consistently use the number of stores that actually sold that specific drug for which the price is recorded. In other words, if in the town of Aberdeen, pharmacy A did not get reimbursed for Adderall through Medicaid, then they are not counted in this measure. I do not know if, for some unobservable reason, pharmacy A does not stock Adderall or would discourage Medicaid patients from buying Adderall, etc. However, the correlation coefficient for the stores in a town that sold a specific drug in the given time period and for *total* stores in that town is a strong 0.923 and the results reported are robust to either measure.

Figure 5.1 contains four graphs that give a sense of the variation in these drug prices. Recall that I have a total of 2,160 coefficients of variation in prices from 26 drugs across 165 markets. Not all drugs were sold in all markets and in some markets there was only one pharmacy that sold a specific drug, therefore it is not the entire set of 4,290 observations possible. The top left panel in Figure 5.1 contains a kernel density estimate which shows that the coefficient of variation is heavily skewed to the right. The remaining three graphs, in clockwise order, show the CV plotted against the mean, the maximum, and the minimum. In all three of these cases it appears that there are some outliers, but the vast majority of the observations indicate that the coefficient of variation is negatively related to the price levels. This is as expected and particularly obvious in the plots of the CV against the mean and the minimum price respectively. Higher price levels should lead to higher propensity to search, which in turn should lead to a convergence in the distribution.

5.4 Econometric Issues

5.4 (a) Heteroscedasticity

A preliminary Ordinary Least Squares regression on the unit price with drug fixed-effects and performing a Breusch-Pagan / Cook-Weisberg test for heteroscedasticity rejects the null hypothesis that the errors have a constant variance (the chi-square statistic for this test was 42.09). A plot of the residuals confirms heteroskedasticity. I now regress the natural log of unit prices on drug fixed effects with drug-clustered robust standard errors, which are an extension to the Huber-White standard errors, and plot the residuals from this regression. Both the residual plot and the Breusch-Pagan test (chi-squared statistic of 1.55), indicate homoscedastic variance in the residuals.[30]

5.4 (b) Intra Class Correlation

According to the literature on intra-class correlation, picking the correct level of clustering needs to be considered. The errors could be correlated across drugs sold at various pharmacies in various towns or correlated across the various pharmacies (i.e. at the pharmacy level instead of drug level, since some might choose to be high priced and therefore all drugs sold at these pharmacies would be higher priced) or they could even be correlated across various towns. In general, not correcting for clustering can lead to a downward bias in the computed standard errors of the regression coefficients. To be prudent, I use both robust standard errors and cluster-robust standard errors allowing for clustering at the drug level for all our regressions.

I expect $E[(\varepsilon_{i,j})(\varepsilon_{i,j+1})] \neq 0$, where i is the i^{th} drug, j is the j^{th} town, and j+1 is a different town i.e. I expect the errors in the data to be correlated since I am looking at the same prescription drugs across a number of different towns. In other words, there may be an unobservable reason that affects the pricing of a specific prescription that is not captured by including a control for the drug itself. Although autocorrelation and serial correlation are used interchangeably in current literature, technically, autocorrelation exists in data when the errors in one series are correlated within themselves. This could happen in two different ways – across periods in time series data and across space, groups, or classes in cross sectional data. Intra class correlation is essentially autocorrelation in cross sectional data. Serial correlation, on the other hand, occurs when

[30] Table A.2 in the appendix shows a comparison of standard errors using unit price versus the natural log of prices as the dependent variable regressed on market characteristics.

the errors from one series are related to errors in a different series. In the recent past, a lot of cross sectional studies tended to ignore autocorrelation mainly because it is difficult to model in a spatial sense.[31] With time series data, it is relatively easy to address with an auto-regressive model since intuitively it seems likely that the errors in the current period are most probably related to the errors in the preceding period. Thus, taking first differences is a practical solution for this problem in time series data.

There are a couple of ways that there could be clustering present in the data. The most obvious is for the pricing of the drugs to be correlated across the pharmacies in various towns as discussed before. However, it is also likely that pharmacy chains themselves adhere to specific pricing strategies and therefore there may be correlation in pharmacy-specific prices for the drugs. In other words, it is entirely possible that Rite-Aid is one of the highest priced sellers across all towns whereas Target positions themselves at the low end of the price distribution of prescription drugs in each town.[32] Furthermore, it is also possible that clustering occurs at the town level.

As expected, I find a high degree of intra class correlation (ICC), at 0.917 across drugs when defined by unit price and 0.954 when defined by the natural log of unit prices. Next, I split the pharmacies up into two broad groups – those that operated independently and those that were part of a chain. I looked for clustering in the drug unit prices across the independently operated pharmacies and then across the chains. I find that the correlation across the independent pharmacies is pretty hefty at 0.806 but even

[31] Rey and Montourri (1999), in a study of U.S. regional income convergence across several decades, reveal strong evidence of misspecification if spatial error dependence is ignored.
[32] Rite Aid and Target are indeed at the high and low end of the price distribution across towns and a result discussed shortly. The fact that Rite Aid is consistently one of the highest priced stores is consistent with the findings of Sorensen (2000) and the data he collected in the state of New York.

higher across the chains. I looked at each chain individually but am only reporting the statistic for all the chains as a group – the ICC was 0.957.[33]

5.5 Empirical Model

5.5 (a) Clustering

The following is a drug fixed effects model I estimate and has as the dependent variable the natural log of price. Explanatory variables include *Number of Pharmacies, Pharmacy Medicaid,* and *Minimum Price.* The purpose of this exploratory regression is to determine the appropriate level of clustering for the standard errors, which are adjusted for clustering at different levels. The results are discussed in section 6.1.

$$LN(PRICE_{ijk}) = \beta_0 + \beta_1 Number\ of\ Pharmacies_{ik} + \beta_2 Pharmacy\ Medicaid_j + \beta_3 Minimum\ Price_{ik} + \beta_4 \sum_{i=1}^{25} \gamma\ DRUG_I + \varepsilon_{ijk} \quad (5.1)$$

5.5 (b) Pharmacy Chains

To see if pharmacy chains follow specific pricing strategies, I run the following regression:

$$LN(PRICE) = \beta_0 + \beta_1 \sum_{i=1}^{26} \alpha\ PHarmacyCHainDummy_i + \beta_2 \sum_{i=1}^{25} \gamma\ DRUGi + \varepsilon \quad (5.2)$$

The results are discussed in section 6.2. The dependent variable is the natural logarithm of unit prices. The coefficients can therefore be interpreted as semi-elasticities. In other words, a one unit change in the independent variable leads to the estimated

[33] I ran a regression on the fixed effects of the drugs on the unit prices of drugs as well as the natural log of the unit prices. I took the residuals from each specification, squared them (since Stata was otherwise truncating them at zero when I used loneway) and looked at the intra class correlation in all the cases mentioned. The intra class correlation for unit prices, as well as the natural log of prices, across drugs was reduced to 0.05 or less, implying that the fixed effects is actually capturing most of the correlation.

coefficient percentage change in the dependent variable, holding all other things constant. Since I only have dummy variables in this specification, the interpretation would be relative to the base case. Given that I have two qualitative regressors, the implicit assumption is that the differential effect of the pharmacy dummy is constant across all drugs and the differential effect of the drug dummy is constant across all pharmacies. While I could use an interaction term to address this limitation, this particular regression is just an exploratory one and does not have any theoretical basis. Thus, it would be beside the point since the main purpose of this dissertation is to determine whether pricing is affected by market characteristics. However, if a lot of pharmacies have specific pricing strategies which are implemented at the chain level, this would work against pricing strategies implemented at the market level and the point of this regression is in making exactly that observation.

5.5 (c) The General Baseline Specifications for Price Levels and Dispersion

I use a drug fixed effects model and from the comparative statics presented in the theoretical section, I get the following.

$$\begin{gathered} \textit{Price- Level}_{ijk} = \beta_0 + \beta_1, \textit{ Number of Pharmacies}_{ik} + \beta_2 \textit{ Search Cost} \\ \textit{Measure At Pharmacy Level} + \beta_3, \textit{ Number of Pharmacies * Search Cost} \\ \textit{Measure At Pharmacy Level}_{ijk} + \varepsilon_{ijk} \end{gathered} \tag{5.3}$$

For the equation presented above for price levels, I control for individual Pharmacy Chains but suppress the coefficients in the output.

For price dispersion,

$$Price\text{-}Dispersion_{ik} = \beta_0 + \beta_1\ Pharmacies_{ik} + \beta_2 Search\ Cost\ Measure\ At\ Town\ Level + \beta_3\ ,\ Number\ of\ Pharmacies\ *\ Search\ Cost\ Measure\ At\ Town\ Level_{ik} + \beta_4 (Search\ Cost\ Measure\ At\ Town\ Level)^2 + \beta_5\ (Number\ of\ Pharmacies_{ik})^2 + \varepsilon_{ik} \qquad (5.4)$$

Where*, Number of Pharmacies* is the number of pharmacies in the k^{th} town that sold the i^{th} drug. *Search Cost Measure At Pharmacy Level* and *Search Cost Measure At Town Level* are measures of the proportion of individuals with either relatively high search costs or low search costs, depending on the measure, as defined in section 5.1 (*Pharmacy Medicaid, Town Medicaid* and then *Online versus Brick and Mortar*), used. *Number of Pharmacies * Search Cost Measure At Pharmacy Level* is the interaction term that captures whether the impact of a higher proportion of positive search cost consumers at a specific pharmacy causes price levels for the i^{th} drug at the j^{th} pharmacy to increase or decrease, as the number of stores in the market increases. A positive coefficient would imply that the marginal effect of a higher proportion of positive search cost consumers at a pharmacy would lead to increased price levels when the number of pharmacies in a market is higher. *Number of Pharmacies * Search Cost Measure At Town Level* is the interaction term that captures whether the impact of a higher proportion of positive search cost consumers in a specific market causes price dispersion for the i^{th} drug in the k^{th} market to change, as the number of stores in the market increases. Here, a positive coefficient would imply that the marginal effect of a higher proportion of positive search cost consumers in a market would lead to increased price dispersion when the number of pharmacies in a market is higher. The squared term for the *Search Cost Measure* variable is included to test for the non-linear, non-monotonic relationship between the price distribution and proportion of individuals with positive search costs. Similarly, the squared term for the *Number of Pharmacies* variable is also included to test for the non-linear, non-monotonic relationship between the price distribution and the number of pharmacies in the market. Regression equations using the specific search cost measures described in section 5.1 are discussed next.

5.5 (d) Using the Medicaid Measures as Proxies for Search Cost Price Level

$$LN(Price)_{ijk} = \beta_0 + \beta_1 Number\ of\ Pharmacies_{ik} + \beta_2\ Pharmacy\ Medicaid + \beta_3 Number\ of\ Pharmacies * Pharmacy\ Medicaid_{ijk} + \varepsilon \tag{5.5}$$

Pharmacy Medicaid is a measure of positive search cost consumers that the j^{th} pharmacy serves. It is a relative measure (relative to other pharmacies in the data set) of the number of drugs that the j^{th} pharmacy sold to Medicaid patients, and is weighted by the popularity of the drug itself. This measure is a proxy for selling prescription drugs in low income neighborhoods since individuals with low income are less likely to have insurance and as a result have high search costs relative to those who have insurance. Thus, we are capturing the Medicaid-neighboring population i.e. people who have a high enough income that disqualifies them from Medicaid but live in the same neighborhood as Medicaid beneficiaries.[34] I also include controls for the various pharmacy chains but the coefficients are suppressed.

[34] While the poverty level for the 48 contiguous states is at over $900 a month for a household of one individual, an income of over $350 per month disqualifies the same household from Medicaid in

From equation 5.5,

$$\frac{\partial(LN(price))}{\partial(Number\ of\ Pharmacies)} = \beta_1 + \beta_3 Pharmacy\ Medicaid \text{ and,}$$

$$\frac{\partial(LN(price))}{\partial(PharmacyMedicaid)} = \beta_2 + \beta_3 Number\ of\ Pharmacies$$

Based on the theory, I expect β_1 to be negative, β_2 to be positive and β_3 to be positive in both cases. In other words, a larger number of pharmacies will have a negative effect with a small proportion of consumers with high search costs, and a positive effect with a high proportion of high search cost consumers, on price levels. Similarly, a larger proportion of high search cost consumers will have a positive impact on price levels with a low number of stores, as well as with a higher number of stores. Furthermore, if we find β_1 to be negative and β_2 to be positive, it will be possible for us to set ∂ln(p)/∂(Number of Pharmacies) = 0, and solve for the value of the search cost variable, Pharmacy Medicaid, when prices are at their lowest levels due to the number of pharmacies in the market. The results are discussed in section 6.3(a).

Price Dispersion

$$Coefficient\ of\ Variation_{ik} = \beta_0 + \beta_1\ (Town\ Medicaid * Number\ of\ Pharmacies)_{ik} + \beta_2\ Town\ Medicaid_k + \beta_3\ Number\ of\ Pharmacies_{ik} + \beta_4 (Town\ Medicaid_k)^2 + \beta_5 (Number\ of\ Pharmacies_{ik})^2 + \varepsilon \qquad (5.6)$$

Coefficient of Variation is the coefficient of variation in the prices of the i^{th} drug in the k^{th} town. The results are discussed in section 6.3(b). *Number of Pharmacies* is again

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Maryland. In all of the counties in Maryland, the county with highest percentage of households with an income at half the poverty level or less was Balimore City at a little over 12 percent. Furthermore, note that it would make little sense for pharmacies to charge higher prices if no one was paying for it.

the number of pharmacies in the k^{th} town that sold the i^{th} drug. I also include the quadratic terms to capture the hypothesized non-linear, non-monotonic relationship between the price dispersion and the respective independent variables in this specification. *Town Medicaid*, which is similar to the search measure *Pharmacy Medicaid*, is now at the town level i.e. it captures the average number of prescription drugs sold to Medicaid beneficiaries in a town and serves as a proxy for low income towns (relative to high income towns in the data set).

Based on theory, I expect β_1 to be positive or negative, β_2 and β_3 to be positive, and β_4 and β_5 to be negative.

From equation 3.6, I get,

$$\frac{\partial(Coefficient\ of\ Variation)}{\partial(Number\ of\ Pharmacies)} = \beta_1 Town\ Medicaid + \beta_3 + 2\ \beta_5\ Number\ of\ Pharmacies$$

and

$$\frac{\partial(Coefficient\ of\ Variation)}{\partial(Town\ Medicaid)} = \beta_1\ Number\ of\ Pharmacies + \beta_2 + 2\ \beta_4 Town\ Medicaid$$

5.5 (e) Online versus Offline as Proxies of Search Cost

Price Level

$$Average\ Markup_{io} = \beta_0 + \beta_1\ Online\ Pharmacy\ Dummy_{\ o} + \beta_2 Maximum\ Price_{io} +\ e \tag{5.7}$$

Average Markup is the average of the markup (as defined in section 5.2) for the i^{th} drug in the o^{th} market. Markets here are defined as online and offline (traditional or brick and mortar). Recall that the online prices and the brick and mortar prices were collected a year apart. Therefore, a direct price comparison is not possible, however, a relative price level comparison using the average markup is valid analysis. I use the maximum price of the i^{th} drug in the o^{th} market, the *Maximum Price* variable, as a control for price levels. The results are discussed in section 6.4(a).

The expected sign for the *Online Pharmacy Dummy* (= 1 means the pharmacy sells online) is negative regardless of how we define the brick and mortar market. There are two possible ways to consider the brick and mortar market. The first is to consider each individual brick and mortar market separately as has been done in the prior sections. The other is to aggregate all the prices for the i^{th} drug from brick and mortar pharmacies and consider all brick and mortar pharmacies as one market.

I do not include the number of pharmacies in this specification since the number of firms (as long as it is greater than one) in an online environment is irrelevant due to zero search costs. This variable is only relevant in a brick and mortar setting where the number of firms is positively correlated to the cost of learning the price distribution. Thus, with geographic location being irrelevant on the internet, there is only one online market.

Price Dispersion

$$\textit{Coefficient of Variation}_{io} = \beta_0 + \beta_1 \textit{ Online Pharmacy Dummy}_o + \beta_2 \textit{Maximum Price}_{io} + e \tag{5.8}$$

The results are discussed in section 6.4(b). Here also, both definitions of the brick and mortar are considered - the first for each individual brick and mortar market and the second for all the brick and mortar pharmacies aggregated into one offline market. The expected sign for *Online Pharmacy Dummy* (= 1 means the pharmacy sells online) is negative. The *Maximum Price* variable is once again used to control for price levels.

5.5 (f) The Price Distribution and the Number of Pharmacies

I construct a couple of quantile regression plots using the CV and the average markup on the y axis, respectively, and the quantiles of the number of firms on the x-axis. This is to ensure that the results are not driven by a few outliers.

Furthermore, I regressed the maximum and minimum prices on the drug fixed effects model and then plotted the residuals from these regressions against the quantiles of the number of firms. The objective is to observe what happens to the maximum and the minimum price as the number of firms in a market increases. These plots are discussed in section 6.5.

5.5 (g) Value of Search

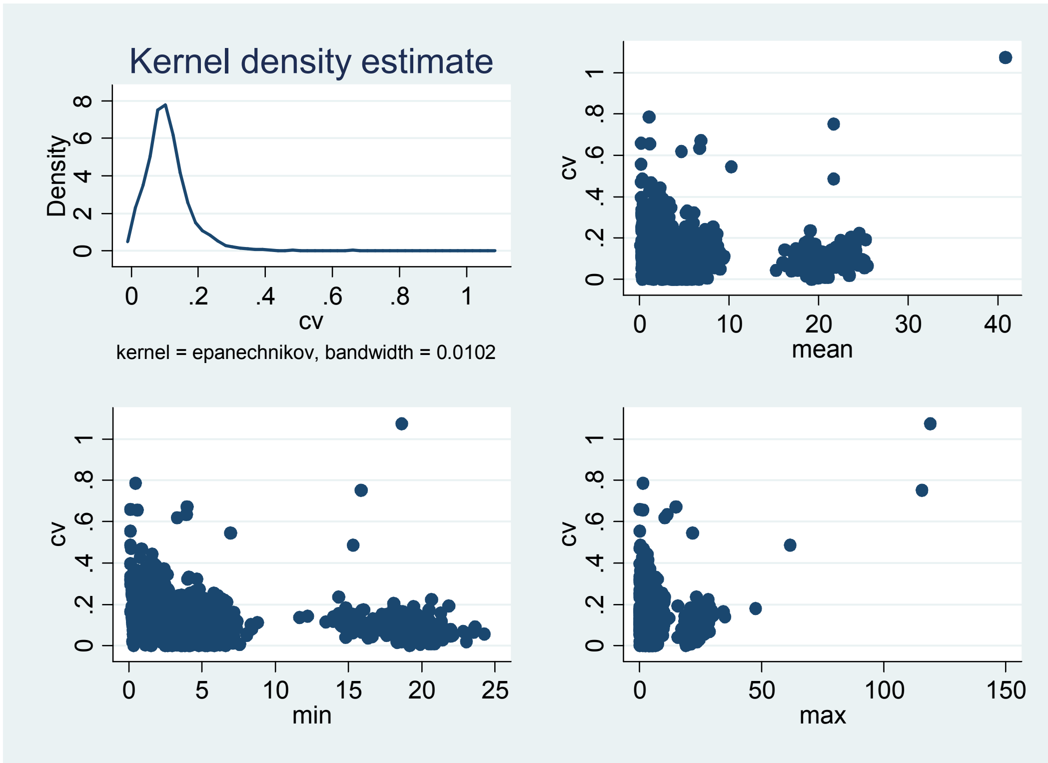
Finally, I look at the benefits of searching for the price of prescription drugs before making a purchase. I define the value of search, via Stahl, as equal to the difference between the expected price i.e. the mean, and the minimum price of the drug normalized by the minimum price in that market.[35] I run the following regression:

$$ValueofSearch_{ik} = \beta_0 + \beta_1 Pharmacies_{ik} + \beta_2 Onlinedummy_o + \varepsilon \qquad (5.9)$$

The value of searching for the ith drug in the kth town is the difference between the expected price and the minimum price as a proportion of the minimum price. I expect the value of search to increase as number of pharmacies increases, and be lower online. The results are discussed in section 6.6.

[35] Although similar, this measure is not the same as the mark up which uses the difference between the *observed* price and the minimum price in the numerator.

Figure 5.1: Coefficient of Variation for the Price of Each Drug by Market.



Top Left Panel – A kernel density plot shows that the distribution of the CV of drug prices are heavily skewed to the right
Top Right Panel – Scatter plot of the coefficient of variation against the mean price
Bottom Left Panel - Scatter plot of the coefficient of variation against the minimum price
Bottom Right Panel – Scatter plot of the coefficient of variation against the maximum price
All summary statistics here are computed for each drug in each market.

6. Results

In this chapter, I present the results from the empirical analysis and the equations presented in section 5.5. We begin with regression results showing the varying levels of clustering, next show that pharmacy chains do implement pricing strategies at the chain level, and then present results based on predictions of the theoretical model.

6.1 Level of Clustering

To determine the appropriate level of clustering, the results from regression equation 5.1 are presented in Table 6.1. The independent variables are *Number of Pharmacies*, the number of pharmacies selling that drug in that town, *Pharmacy Medicaid*, which is a crude relative measure of the Medicaid business that the pharmacy gets, *Minimum Price* which is the minimum price of the i^{th} drug in the k^{th} town, and fixed effects for drugs. The robust standard errors (column 2) are only about 15% larger, on average, than the non-robust standard errors (column 1). The standard errors allowing for clustering on drugs (column 3) as well as the ones allowing for clustering on pharmacies (column 4) are much larger at about four times as large as the ones in column 1. Finally, the ones allowing for clustering at the town (column 5) level are about twice as big as the ones in column 1. However, even with the most conservative standard errors, all coefficients are significant at the 1% level. Once again, I observe that the number of stores in a town, ceteris paribus, has a positive impact on the price of the drug. The *Minimum Price* variable is for the minimum price of drug i in town k and is used as a control for price levels of prescription drugs across towns.

6.2 Pharmacy Chain Pricing

The results for regression equation 5.2 are presented in table 6.2. The first column presents a drug and pharmacy chain fixed effects model. I also present estimates using a fixed effects model with robust standard errors, a fixed effects model allowing for clustering across drugs in generating standard errors, a robust regression model and a reproduction of the first specification, i.e. a fixed effects model but with forty two observations dropped (and as explained shortly). I see considerable differences in the standard errors in the three models, with the most conservative ones being generated by the fixed effects with cluster-robust standard errors (column 3). In fact, the robust standard errors (column 2) are, on average, about the same size as the regular, non-robust standard errors (column 1) but only about half as big as the cluster-robust standard errors (column 3). In spite of these large differences in the computed standard errors, there is not a considerable impact on the statistical significance of the estimated coefficients. For example, the coefficient for the Giant Foods Supermarket chain was statistically significant at the 1% level with the first two specifications but with clustered standard errors almost five times larger, fails to remain so. I observe this same phenomenon for Walgreens as well.

The fourth column in the table presents estimates using a “robust” regression technique. As explained earlier, this method uses iteratively reweighted least squares with higher weight given to better behaved observations and little weight given to outlying observations. For my data set, this is an excellent technique, particularly since some of the prices might be skewing the results. However, I find that most of the estimates do not change significantly other than the coefficient for Costco, which now implies that prices, on an average, are lower than prices at independent pharmacies by about 9.49% instead of 71.6%. I also see the coefficient for Target decrease in magnitude, implying that prices are lower on average by 12.8% rather than 15.2%, relative to prices at independent pharmacies. Prices of some drugs were well below the average, especially at Costco, thus driving this result.[36] However, overall, the estimates appear to be quite robust given the econometric rigor.[37]

The fifth column gives estimates with forty two observations dropped. These observations were for the seven drugs – Depakote, Flonase, Fosamax, Norvasc, Pravachol, Wellbutrin and Zoloft. The prices were from six Costco locations in Beltville, Hanover, Frederick, Gaithersburg, Glen Burnie and Chestertown. I dropped these prices because all of these prices were about 10% to 20% of the *mean* price for the drug in that town. In other words, the average prices of these drugs, in those specific towns, were at least a multiple of five times the price listed at Costco. However, as stated in footnote 27, this does not seem accurate. I do not drop the other observations from Costco since they are all within two standard deviations of the mean.

The model presented explains 96.6% (98.3% and 97.6% according to the Robust Regression and the Costco adjusted specifications, respectively) of the variation in the natural log of the prices of prescription drugs. I have dummy variables for the pharmacy

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[36] I take a close look at the Costco prices and find that for some drugs Costco's price seemed unreasonably low. For Pravachol, for example, Costco was charging $18 at all six locations in Maryland that sold this drug. However, the average price of this drug across all pharmacies is $162. It is possible that Costco is reporting the price of a generic equivalent. However, I keep these observations in the first four specifications with the caveat that the coefficients from the robust regression may be more believable for this particular pharmacy chain.

[37] Note that I am only looking at brick and mortar pharmacies here and not any of the online sellers. I also ran a set of the same regressions but now included dummy variables for the online firms. The estimated coefficients as well as standard errors from the results presented were practically identical. Recall that the key reason I wanted to run this regression was to see if pharmacy chains had any chain-wide pricing policies since this would then affect dispersion measures at the town-level. This precludes the need for online sellers to be included in these estimates.

chains and for each individual drug in estimating this equation. For the pharmacy chain dummies, I lumped all the independent pharmacies into one category and made that the base case. The remaining twenty six dummy variables are for each actual pharmacy chain such as CVS, Walgreens, etc. A lot of the pharmacy chains have significantly higher or lower pricing strategies than the independent stores. As mentioned, of the major chains, Target and Costco appear to be the lowest priced with prices an average of 15% and 13% lower than the independent pharmacies, respectively. Rite Aid on the other hand, appears to be one of the highest priced major chains with prices on an average about 9% above the independent stores. There are significantly different prices for the prescription drugs as well. Adderall was dropped due to collinearity issues. I had specified Prevacid as the base case justified strictly on the fact that I had the most observations for this drug.

If a lot of pharmacies have specific pricing strategies which are implemented at the chain level, this could work against pricing strategies implemented at the market level and the point of this regression is in making exactly this observation.[38] I find this to be largely true for the various pharmacy chains i.e. Rite-Aid is one of the highest priced chains whereas Target is one of the lowest-priced.

6.3 Using the Crudeaid Measures as Proxies for Search Cost

6.3 (a) Price Level

The results from equation 5.5 are presented in Table 6.3(a). I use robust standard errors as well as drug clustered standard errors. While the drug clustered standard errors are slightly more conservative, the changes in the sizes of the standard errors are not

[38] A frequency distribution of the prices of the drug Flonase at ninety nine Rite-Aids in Maryland is presented in table A.3 in the appendix. I observe a total of fifteen prices, with two of these prices accounting for half the occurrences in this sample. This is a typical pricing pattern for the chain pharmacies.

enough to affect the levels of statistical significance for any of the coefficients. While the interaction term is not significant, the search cost variable, *Pharmacy Medicaid*, and the *Number of Pharmacies* in the market are both significant at 0.01 and 0.10 levels, respectively. All three of the terms are positive. I also run the regression without five drugs that were in non-pill forms of delivery i.e. inhalers, liquid drops, etc. The consideration was that since all the drugs are supposed to be for a 30 day period, the non-pill forms might lead to some ambiguity in the quantity prescribed and consumed over this specific period. *Pharmacy Medicaid* continues to be significant at the 0.01 level, but the *Number of Pharmacies* is no longer significant.

From equation 5.5, I get,

$$\frac{\delta(LN(price))}{\delta(Number\ of\ Pharmacies)} = \beta_1 + \beta_3\,Pharmacy\ Medicaid = 0.00048 + .0026\,(Pharmacy\ Medicaid). \qquad (6.1)$$

The search cost variable, Pharmacy Medicaid, ranges in the data from 0.015 to 0.87. Recall that this measure is an index, so they only convey meaning when compared within the index. The mean of this measure is 0.416 and the standard deviation is 0.146. Using equation 6.1, I compute the marginal effects. These are presented in table 6.3(b). Based on the table (or equation 6.1), given the range in this data for Pharmacy Medicaid, an increase in the number of pharmacies will lead to an increase in price level, although the magnitude of the increase will depend on the proportion of positive search cost consumers in the market.

Also from equation 5.5, we get,

$$\frac{\partial(LN(price))}{\partial(PharmacyMedicaid)} = \beta_2 + \beta_3 Number\ of\ Pharmacies = 1.564 + .0026(Number\ of\ Pharmacies) \qquad (6.2)$$

β_2 and β_3 are positive as expected. The *Number of Pharmacies* in this data set ranges from 1 to 49 in a given market. The mean for this variable is 11.595 and the standard deviation is 10.9 implying a distribution skewed heavily to the right. Thus, I use values of 2, 5, 10, 20, 30, and 40 for *Number of Pharmacies* and using equation 6.2, I compute the marginal effects. These are presented in Table 6.3(c). An increase in the proportion of consumers with positive search costs would lead to an increase in price levels. *Pharmacy Medicaid*$_j$ is a measure of positive search cost consumers that the j^{th} pharmacy serves. It is a relative measure (relative to other pharmacies in the data set) of the number of drugs that the j^{th} pharmacy sold to Medicaid patients. This measure is a proxy for selling prescription drugs in low income neighborhoods since individuals with low income are less likely to have insurance and as a result have high search costs relative to those who have insurance.[39]

6.3 (b) Price Dispersion

The results from equation 5.4 are presented in Table 6.4. The first column shows the estimates with just the independent variables *Number of Pharmacies* and *Town Medicaid*. The second column adds in the interaction variable, *Town Medicaid * Number of Pharmacies,* and the third column further adds in the squared terms to show the estimates for the complete specification presented in equation 5.4. I note that the r-squared does not change across the three columns and due to the highly correlated nature of the interaction and squared terms with the independent variables, multicollinearity appears to be causing problems with the estimates. The relationship between price dispersion and the number of pharmacies in the market may be monotonic, as opposed to

[39] This result is not driven by the 340B program which reimburses contracting pharmacies via dispensing fees and does not allow pharmacies to mark-up prices to generate revenue.

non-monotonic, as predicted by the theoretical model. I explore this implication further in section 6.4. *Number of Pharmacies* is not statistically significant. However, when the regression was run without the interaction term or the squared term, it was significant at the 0.01 level. *Town Medicaid*, which is similar to the search measure *Pharmacy Medicaid*, is now at the town level i.e. it captures the average number of prescription drugs sold to Medicaid beneficiaries in a town and serves as a proxy for low income towns (relative to high income towns in the data set). The *Town Medicaid* variable is statistically insignificant. However, when the regression was run without the interaction term or the squared term, it was significant at the 0.01 level.

From regression equation 6.4, we get,

$$\frac{\delta(Coefficient\ of\ Variation)}{\delta(Number\ of\ Pharmacies)} = \beta_1 Town\ Medicaid + \beta_3 + 2\ \beta_5\ Number\ of\ Pharmacies =$$

$$0.00387(Town\ Medicaid) - 0.00151 - (2)(0.00000672)(Number\ of\ Pharmacies)$$

and

$$\frac{\delta(Coefficient\ of\ Variation)}{\delta(Town\ Medicaid)} = \beta_1\ Number\ of\ Pharmacies + \beta_2 + 2\ \beta_4 Town\ Medicaid =$$

$$0.00387\ (Number\ of\ Pharmacies) - 0.622 - (2)(30.62)(Town\ Medicaid)$$

We do not compute marginal effects because introducing the squared and interaction terms is leading to severe multicollinearity issues.

6.4 Online versus Offline as Proxies of Search Cost

6.4 (a) Price Level

The results are presented in Table 6.5. I present two sets of results. The first column presents results with each individual brick and mortar market being treated as such and comparing these individual brick and mortar markets to the online market. The second column aggregates all offline pharmacies into one brick and mortar market and then compares this sole brick and mortar market to the online market. The expected sign for *Online Pharmacy Dummy* (= 1 means the pharmacy sells online) is negative and it is so and statistically significant at the 1% level regardless of how I define the brick and mortar market. However, the r-squared is much higher in the case where I aggregated the brick and mortar pharmacies into one market.

I do not include the number of pharmacies in this specification since the number of firms (as long as it is greater than one) in an online environment is irrelevant due to zero search costs. This variable is only relevant in a brick and mortar setting where the number of firms is positively correlated to the cost of learning the price distribution. Thus, with geographic location being irrelevant on the internet, there is only one online market.

6.4 (b) Price Dispersion

$$CV_{io} = \beta_0 + \beta_1\, DOnlinePharmacy_o + \beta_2 MaxPrice_{io} + \varepsilon$$

The results are presented in Table 6.6. Once again, I present two sets of results, one for each individual brick and mortar market and one for all the brick and mortar pharmacies aggregated into one offline market. Here also, the expected sign for *DOnlinePharmacy* (= 1 means the pharmacy sells online) is negative and it is so and statistically significant at the 1% level regardless of how I define the brick and mortar market. The *Maximum Price* variable is once again used to control for price levels.

6.5 The Price Distribution and the Number of Pharmacies

In Figure 6.1 and 6.2, I construct a couple of quantile regression plots using the *Coefficient of Variation* and the *Average Markup* on the y axis, respectively, and the quantiles of the *Number of Pharmacies* on the x-axis. I am able to observe the clear trend that both *Coefficient of Variation* as well as the *Average Markup* increase as the number of firms in a market increases. This further confirms that these results are not driven by a few outliers.

Furthermore, I regressed the *Maximum Price* and the *Minimum Price* on the drug fixed effects model and then used the residuals from these regressions in Figure 6.3 and Figure 6.4, on the y-axis respectively, and the quantiles of the *Number of Pharmacies* on the x-axis. The distinctive trend in both cases is for *Maximum Price* to increase and *Minimum Price* to decrease as the *Number of Pharmacies* in a market increases.

Not only does the *Coefficient of Variation* increase as the *Number of Pharmacies* increases, I also observe the upper support of the distribution increasing and the lower support of the distribution decreasing. This is a more complete visual of the evolving price distribution than just looking at any individual measure of dispersion. Thus, not only do I observe Stahl's prediction, given positive search cost consumers, come true, I also observe the competitive outcome hold. It seems feasible that with a large number of firms in a particular market, some may adopt a different strategy than others.

6.6 Value of Search

Finally, I look at the benefits of searching for the price of prescription drugs before making a purchase. I define the value of search, via Stahl, as equal to the difference between the expected price i.e. the mean, and the minimum price of the drug normalized by the minimum price in that market.[40] I run the following regression:

$$ValueofSearch_{ik} = \beta_0 + \beta_1 Pharmacies_{ik} + \beta_3 Onlinedummy_o + \varepsilon$$

The value of searching for the ith drug in the kth town is the difference between the expected price and the minimum price as a proportion of the minimum price. I expect the value of search to increase as number of pharmacies increases. The results are presented in table 6.7. The coefficient is indeed positive and significant at the 0.01 level. I expect the value of search to be lower for those searching online when compared to those searching offline. The coefficient is indeed negative and significant at the 0.01 level. The R-squared for this regression is 0.3022, therefore, about thirty percent of the variation in the dependent variable is explained by the variation in the independent variables.

[40] Although similar, this measure is not the same as the mark up which uses the difference between the *observed* price and the minimum price in the numerator.

Table 6.1: LN(Unit price) on Market Characteristics

Dependent Variable	*Ln(price)* *(1)*	*Ln(price)* *(2)*	*Ln(price)* *(3)*	*Ln(price)* *(4)*
Number of Pharmacies	0.00206***	0.00206***	0.00206***	0.00206***
	(0.000112)	(0.000230)	(0.000419)	(0.000235)
Pharmacy Medicaid	2.359***	2.359***	2.359***	2.359***
	(0.144)	(0.475)	(0.459)	(0.295)
Minimum Price	0.0494***	0.0494***	0.0494***	0.0494***
	(0.00188)	(0.0137)	(0.00807)	(0.00404)
Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	No	Yes (Drug)	Yes (Pharmacy)	Yes (Town)
Observations	14,741	14,741	14,741	14,741
R-squared	0.972	0.972	0.972	0.972

1.Robust Standard errors in parentheses.

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

Table 6.2: LN(Unitprice) on pharmacy and drug fixed effects.[41]

Dependent Variable	*Ln(price)* (1)	*Ln(price)* (2)	*Ln(price)* (3)	*Ln(price)* (4)	*Ln(price)* (5)
BJ'S WHOLESALE	-0.249***	-0.249***	-0.249***	-0.247***	-0.253***
	(0.0547)	(0.0249)	(0.0250)	(0.0383)	(0.0460)
CVS INC	0.0318***	0.0318***	0.0318***	0.0403***	0.0321***
	(0.00381)	(0.00329)	(0.0105)	(0.00267)	(0.00320)
COSTCO	-0.716***	-0.716***	-0.716***	-0.0949***	-0.131***
	(0.0134)	(0.0793)	(0.200)	(0.00940)	(0.0139)
ECKERD DRUG	0.0291***	0.0291***	0.0291**	0.0344***	0.0294***
	(0.00896)	(0.00665)	(0.0120)	(0.00626)	(0.00752)
ENSIGN PHARMACIES	0.0726***	0.0726***	0.0726***	0.0671***	0.0725***
	(0.0173)	(0.0163)	(0.0204)	(0.0121)	(0.0146)
FELDMAN'S	-0.00925	-0.00925	-0.00925	0.0183	-0.00998
	(0.0257)	(0.0230)	(0.0236)	(0.0180)	(0.0216)
FOOD LION	-0.152***	-0.152***	-0.152***	-0.149***	-0.154***
	(0.0374)	(0.0200)	(0.0247)	(0.0262)	(0.0314)
GIANT FOOD	-0.0128***	-0.0128***	-0.0128	-0.0228***	-0.0123***
	(0.00426)	(0.00412)	(0.0242)	(0.00298)	(0.00357)
HAPPY HARRYS	-0.000300	-0.000300	-0.000300	0.0122	0.000754
	(0.0130)	(0.00893)	(0.0173)	(0.00907)	(0.0109)
HOME CARE	-0.0374**	-0.0374***	-0.0374***	-0.0218**	-0.0365***
	(0.0156)	(0.00940)	(0.0121)	(0.0109)	(0.0131)

[41] Coefficient for drug fixed effects are suppressed in columns 1, 2 and 5. We presented these coefficients in columns 3 and 4 simply to show that there are no extreme observations that are driving the results, as was the case with the Costco prices. Also, the highlighted coefficients within the table show a change in statistical significance.

Table 6.2(continued): LN(Unitprice) on pharmacy and drug fixed effects.

Dependent Variable	*Ln(price)*	*Ln(price)*	*Ln(price)*	*Ln(price)*	*Ln(price)*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
K MART	-0.0828***	-0.0828***	-0.0828***	-0.0737***	-0.0821***
	(0.00994)	(0.00760)	(0.0125)	(0.00695)	(0.00835)
KLEINS PHARM	-0.0541***	-0.0541***	-0.0541***	-0.0389***	-0.0543***
	(0.0156)	(0.0111)	(0.0185)	(0.0109)	(0.0131)
MARTINS PHARMACY	-0.0562***	-0.0562***	-0.0562***	-0.0501***	-0.0546***
	(0.0160)	(0.00871)	(0.0102)	(0.0112)	(0.0134)
METRO PHARMACY	-0.0937***	-0.0937***	-0.0937***	-0.0835***	-0.0940***
	(0.0143)	(0.0102)	(0.0138)	(0.0100)	(0.0120)
NEIGHBORCARE PHARMACIES	0.0673***	0.0673***	0.0673***	0.0782***	0.0678***
	(0.00772)	(0.00560)	(0.0106)	(0.00540)	(0.00649)
RITE AID	0.0915***	0.0915***	0.0915***	0.0981***	0.0912***
	(0.00407)	(0.00335)	(0.0112)	(0.00284)	(0.00342)
SAFEWAY INC	-0.0445***	-0.0445***	-0.0445***	-0.0334***	-0.0446***
	(0.00562)	(0.00391)	(0.00718)	(0.00393)	(0.00472)
SHOPPERS PHARMACY	-0.0880***	-0.0880***	-0.0880***	-0.0742***	-0.0884***
	(0.0122)	(0.00816)	(0.0109)	(0.00855)	(0.0103)
SUPER FRESH	-0.0717***	-0.0717***	-0.0717***	-0.0571***	-0.0720***
	(0.0120)	(0.0108)	(0.0147)	(0.00841)	(0.0101)
SAMS EAST	-0.361***	-0.361***	-0.361***	-0.294***	-0.361***
	(0.0215)	(0.0349)	(0.0481)	(0.0150)	(0.0180)

Table 6.2(continued): LN(Unitprice) on pharmacy and drug fixed effects.

Dependent Variable	*Ln(price)* (1)	*Ln(price)* (2)	*Ln(price)* (3)	*Ln(price)* (4)	*Ln(price)* (5)
TARGET DRUG	-0.152***	-0.152***	-0.152***	-0.128***	-0.152***
	(0.00900)	(0.00857)	(0.0229)	(0.00629)	(0.00756)
THE MEDICINE	0.0379***	0.0379***	0.0379***	0.0226***	0.0381***
	(0.00773)	(0.00835)	(0.00898)	(0.00540)	(0.00649)
TWIN KNOLLS	-0.126***	-0.126***	-0.126**	-0.0444***	-0.125***
	(0.0242)	(0.0392)	(0.0638)	(0.0169)	(0.0203)
WAL-MART PHARMACY	-0.131***	-0.131***	-0.131***	-0.0980***	-0.131***
	(0.00622)	(0.00644)	(0.0243)	(0.00435)	(0.00522)
WALGREENS	0.0199**	0.0199***	0.0199	0.0258***	0.0206***
	(0.00838)	(0.00504)	(0.0154)	(0.00586)	(0.00704)
WEIS PHARMACY	-0.0653***	-0.0653***	-0.0653***	-0.0613***	-0.0647***
BJ'S WHOLESALE	(0.00984)	(0.00768)	(0.0149)	(0.00688)	(0.00826)
Adderall XR			-0.0547***	-0.0597***	
			(0.00158)	(0.00560)	
Advair Discus			-0.477***	-0.479***	
			(0.000579)	(0.00531)	
Albuterol			-1.357***	-1.342***	
			(0.00178)	(0.00529)	
Celebrex			-1.046***	-1.105***	
			(0.00187)	(0.00624)	
Combivent			0.232***	0.219***	
			(0.000577)	(0.00536)	

Table 6.2(continued): LN(Unitprice) on pharmacy and drug fixed effects.

Dependent Variable	*Ln(price)* (1)	*Ln(price)* (2)	*Ln(price)* (3)	*Ln(price)* (4)	*Ln(price)* (5)
Concerta			-0.139***	-0.153***	
			(0.00157)	(0.00541)	
Depakote			-0.551***	-0.490***	
			(0.00185)	(0.00605)	
Flonase			0.0346***	0.0455***	
			(0.000513)	(0.00510)	
Fosamax			1.323***	1.336***	
			(0.000334)	(0.00515)	
Furosemide			-2.909***	-2.889***	
			(0.00354)	(0.00651)	
Lexapro			-0.540***	-0.540***	
			(0.000426)	(0.00517)	
Lipitor			-0.635***	-0.640***	
			(0.000293)	(0.00500)	
Lotrel			-0.469***	-0.468***	
			(0.00156)	(0.00715)	
Nexium			-0.0278***	-0.0318***	
			(0.00198)	(0.00627)	
Norvasc			-0.844***	-0.831***	
			(0.000638)	(0.00527)	
Ortho Evra			1.175***	1.164***	
			(0.00114)	(0.00531)	

Table 6.2(continued): LN(Unitprice) on pharmacy and drug fixed effects.

Dependent Variable	*Ln(price)*	*Ln(price)*	*Ln(price)*	*Ln(price)*	*Ln(price)*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Plavix			-0.142***	-0.153***	
			(0.00345)	(0.00598)	
Pravachol			-0.123***	-0.105***	
			(0.000869)	(0.00551)	
Risperdal			-0.0902***	-0.0832***	
			(0.00150)	(0.00593)	
Seroquel			-0.218***	-0.212***	
			(0.00112)	(0.00568)	
Singulair			-0.369***	-0.373***	
			(0.00204)	(0.00582)	
Toprol XL			-1.587***	-1.589***	
			(0.00106)	(0.00557)	
Wellbutrin XL			-0.0571***	-0.0531***	
			(0.000900)	(0.00562)	
Zetia			-0.604***	-0.619***	
			(0.00241)	(0.00646)	
Zoloft			-0.590***	-0.577***	
			(0.000543)	(0.00526)	
Standard Errors		Robust	Drug Clustered		
Special Case				Robust Regression	Costco Adjusted
Observations	14,487	14,487	14,487	14,487	14,445
R-squared	0.966	0.966	0.966	0.983	0.976

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.3(a): LN(Unit Price) on positive search cost consumers

Dependent Variable	*ln(Price)* *(1)*	*ln(Price)* *(2)*	*ln(Price)* *(3)*
(Pharmacy Medicaid) X(Number of Pharmacies)	0.0026	0.0026	0.0045
	(0.00838)	(0.0084)	(0.00916)
Pharmacy Medicaid	1.564***	1.564***	0.0914***
	(0.169)	(0.495)	(0.186)
Number of Pharmacies	0.00048*	0.00048*	0.00029
	(0.00028)	(0.00026)	(0.00032)
Fixed Effects	Yes	Yes	Yes
Clustered	No	Yes (Drug)	Yes(Drug)
Special Case	No	No	Dropped 5 Drugs
Observations	14,741	14,741	11,386
R-squared	0.975	0.975	0.9761

Robust standard errors in parentheses

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

Table 6.3(b): Marginal Effects of Number of Pharmacies on Price Levels

	Values for Pharmacy Medicaid	**Marginal Effects for ∂ln(p)/∂(Number of Pharmacies)**
3 Standard deviations below mean	0.0151467	0.000519381
2 Standard deviations below mean	0.1188639	0.000789046
1 Standard deviations below mean	0.2674252	0.001175306
At the mean	0.4159865	0.001561565
1 Standard deviations above mean	0.5645478	0.001947824
2 Standard deviations above mean	0.7131091	0.002334084
3 Standard deviations above mean	0.8616704	0.002720343

Table 6.3(c): Marginal Effects of Pharmacy Medicaid on Price Levels

Values for Number of Pharmacies	Marginal Effects for ∂ln(p)/∂(Pharmacy Medicaid)
2	1.5692
5	1.577
10	1.59
20	1.616
30	1.642
40	1.668

Table 6.4: Coefficient of Variation with Positive Search Cost Consumers

Dependent Variable	*Coefficient of Variation (1)*	*Coefficient of Variation (2)*	*Coefficient of Variation (3)*
Number of Pharmacies	0.000818***	-0.000930	-0.00151
	(0.000290)	(0.000842)	(0.00113)
Town Medicaid	2.011***	1.949***	-0.622
	(0.432)	(0.421)	(1.259)
(Town Medicaid) X (Number of Pharmacies)		0.00264**	0.00387***
		(0.00122)	(0.00133)
(Pharmacies)^2			-6.72e-06
			(1.68e-05)
(Town Medicaid)^2			30.62*
			(15.33)
Observations	2,160	2,160	2,160
R-squared	0.176	0.177	0.179

Robust Standard errors in parentheses. All specifications are estimated using fixed effects and clustering by drug.

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

Table 6.5: Online versus Offline Price Markup

Dependent Variable	*Average Markup*	*Average Markup*
Observational Unit	Individual Brick and Mortar	Online Sites & Single Offline Market
Online Pharmacy Dummy	-0.0733***	-0.434***
	(0.0103)	(0.0773)
Maximum Price	0.0103***	0.000724
	(0.00329)	(0.00157)
Observations	2,160	50[42]
R-squared	0.200	0.830

Standard errors in parentheses. All specifications are estimated using fixed effects and clustering by drug.

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

[42] *Albuterol was not available at any of the online pharmacies. Including the observation does not change the results in any meaningful way and the estimates are available upon request.*

Table 6.6: Online versus Offline Price Dispersion

VARIABLES	*Coefficient of Variation*	*Coefficient of Variation*
Observational Unit	Individual Brick and Mortar	Online Sites & Single Offline Market
Online Pharmacy Dummy	-0.0679***	-0.0799***
	(0.00679)	(0.0129)
Maximum Price	0.0103***	0.00198***
	(0.00164)	(0.000248)
Observations	2,160	50
R-squared	0.353	0.908

Standard errors in parentheses. All specifications are estimated using fixed effects and clustering by drug.

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

Table 6.7: Value of search as the dependent variable

VARIABLES	*Value of search*
Number of Pharmacies	0.00984***
	(0.00147)
Online Pharmacy Dummy	-0.129***
	(0.0151)
Observations	2,160
R-squared	0.302

Robust standard errors in parentheses. All specifications are estimated using fixed effects and clustering by drug.

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

Figure 6.1: Quantile Regression Plot of the Coefficient of Variation on Number of Pharmacies

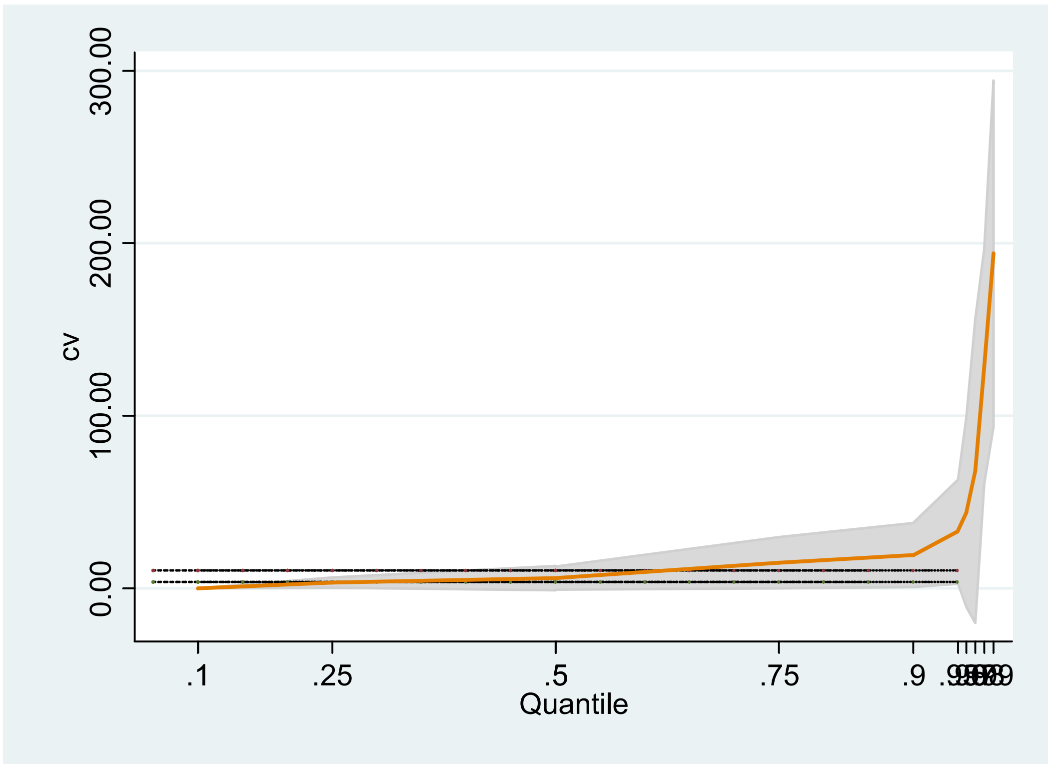


Figure 6.2: Quantile Regression Plot of the Average Markup on Number of Pharmacies

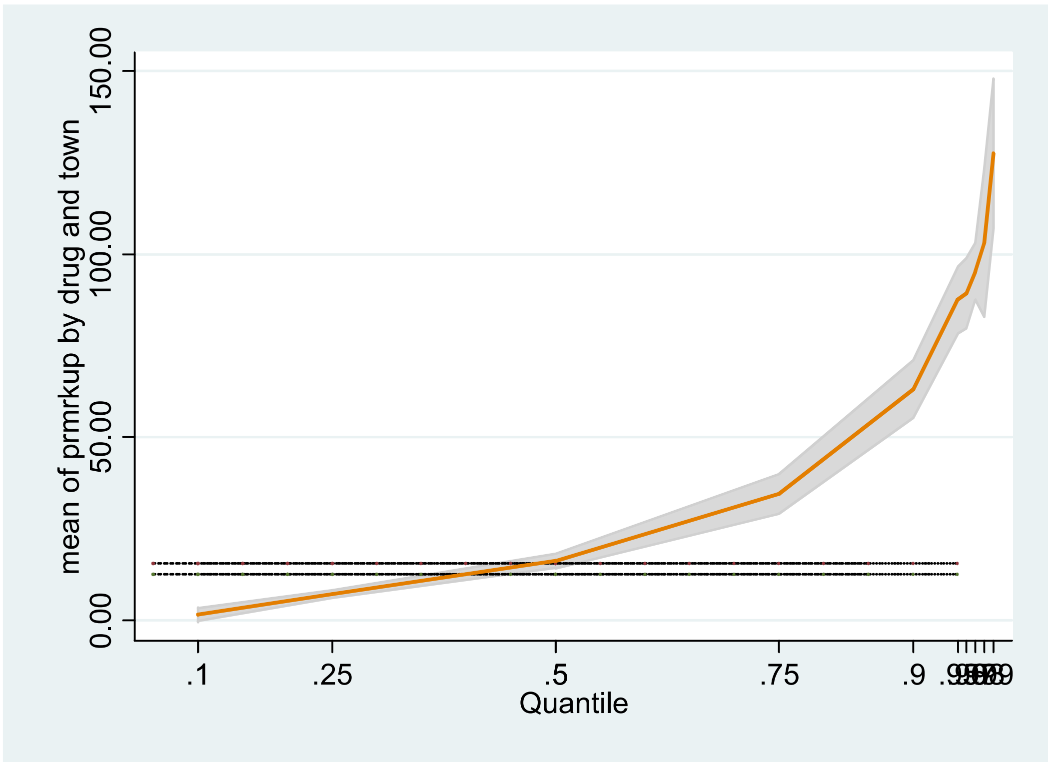


Figure 6.3: Quantile Regression Plot of Residuals from Maximum Price on Number of Pharmacies

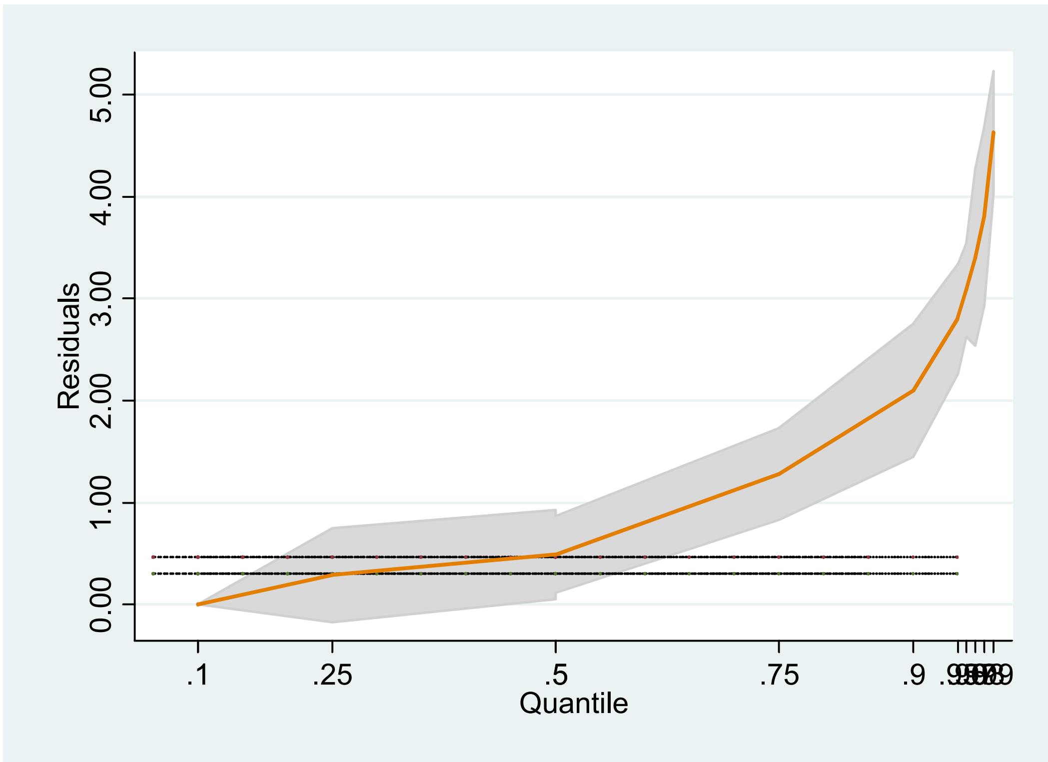
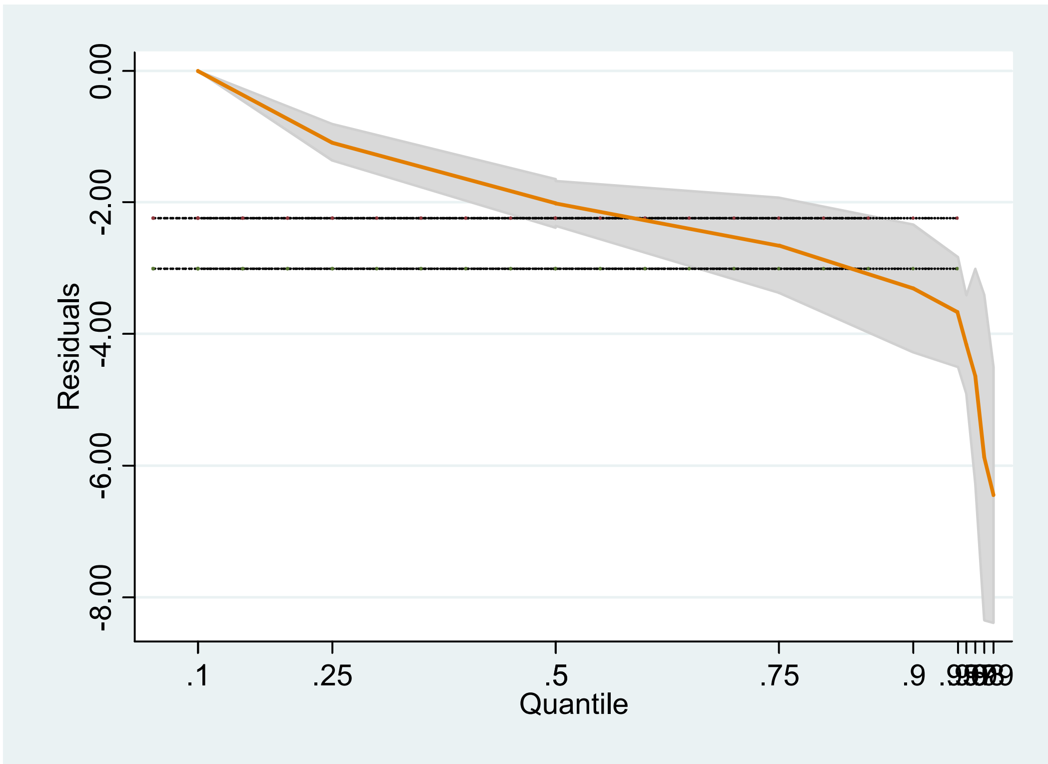


Figure 6.4: Quantile Regression Plot of Residuals from the Minimum Price on Number of Pharmacies



7. Conclusion

For retail prescription drugs, I look at online versus offline price levels and dispersion, as well as price levels and dispersion in purely offline markets from the structure of the market context. I use Stahl (1989) to formulate the testable hypotheses that as the proportion of positive search cost consumers increases from zero up to a certain threshold, price dispersion will increase. Beyond that threshold, price dispersion will decrease. Price levels will, however, increase continuously as the proportion of positive search cost consumers goes from zero to one. Furthermore, in markets with a sufficient proportion of high search cost consumers, an increase in the number of pharmacies will result in an increase in prices to the point that the price distribution degenerates to the monopoly price. This is contradictory to the competitive outcome, where consumers are assumed to have perfect information, and an increase in the number of pharmacies leads to marginal cost pricing.

I look at specific drugs that are of the same strength and package size. Thus the physical product itself is homogeneous. This allows for a more consistent comparison of prices across various retailers. It also allows for a more powerful cost benefit analysis since the benefit from the drug itself is identical whereas the cost is a function of where the drug is bought. In short, it would be difficult to dispute that a tablet of Lipitor 20 mg will provide the same benefit, regardless of whether it is bought at Walgreens or Wal-Mart, while at the same time, the difference in prices paid by the consumer is perfectly observable and can be quite considerable.

For analysis, I use two different measures to proxy for heterogeneous search costs. In one, I look at prices at online pharmacies and compare those to prices at brick and mortar pharmacies. The intuition behind this comparison is that it is much easier and thus less costly to search online than it is to search at brick and mortar stores. As expected, I find more competitive price levels as well as lower price dispersion in the online pharmacies relative to the brick and mortar pharmacies.

The other measure that proxies heterogeneous search costs is the Medicaid measure. This measure captures pharmacies that are serving a relatively higher proportion of Medicaid beneficiaries. The point of this measure is that a pharmacy serving a higher number of Medicaid beneficiaries would also be serving those living in the same neighborhood and who make more than $350 a month and thus do not qualify for Medicaid in Maryland. These consumers are also less likely to have prescription drug coverage, which makes them consumers with high search costs. As expected, I observe higher prices in pharmacies serving a greater proportion of high search cost consumers. I also find that price dispersion increases in markets with a greater number of pharmacies. This is contrary to expectations based on the theoretical model which predicts a non-monotonic relationship between the number of firms and the observable dispersion in prices.

The major conclusion of this work is that given the degree of dispersion observable in prescription drug prices, making price information more transparent will result in a more competitive outcome. The posting of prescription drug prices needs to be consistent and the availability of this information needs to be marketed so that consumers are aware of the resources available to help them make informed choices. From a policy perspective, greater emphasis should be placed in making markets more competitive where feasible.

APPENDIX

Table A.1: Top 5 U.S Pharmaceutical Products by Sales in billions of dollars

		2009	***2008***	***2007***	***2006***	***2005***
Total US Prescription Market	**Drug Name**	**300.3**	**285.7**	**280.5**	**270.3**	**247.3**
1	LIPITOR	7.5	7.8	8.1	8.6	8.2
2	NEXIUM	6.3	5.9	5.4	5.1	4.3
3	PLAVIX	5.6	4.8	3.9	2.9	3.5
4	ADVAIR DISKUS	4.7	4.4	4.2	3.9	3.5
5	SEROQUEL	4.2	3.8	3.4	3.0	2.5

Source: IMS National Sales Perspectives

Table A.2: Unit price and LN(price) on Number of Pharmacies

Dependent Variables	unitprice	lnprice	lnprice	lnprice
Number of Pharmacies	0.00929***	0.00138***	0.000495***	0.00124***
	(0.00262)	(0.000157)	(0.000107)	(9.23e-05)
Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes (Drug)	Yes (Drug)	Yes (Pharmacy)	No
Special Case				Robust Regression
Observations	14,741	14,741	14,741	14,741
R-squared	0.921	0.969	0.978	0.976

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Price and Price Frequencies of Flonase 50 mcg at various Rite-Aid Pharmacies in Maryland.

Price	Frequency
5.874375	1
6.186875	3
6.311875	7
6.436875	1
6.499375	4
6.561875	11
6.686875	22
6.811875	1
6.936875	3
7.061875	3
7.186875	1
7.436875	4
7.499375	8
7.624375	27
7.749375	3

Figure A.1: Residuals from Drug Fixed Effects on Unit Price.

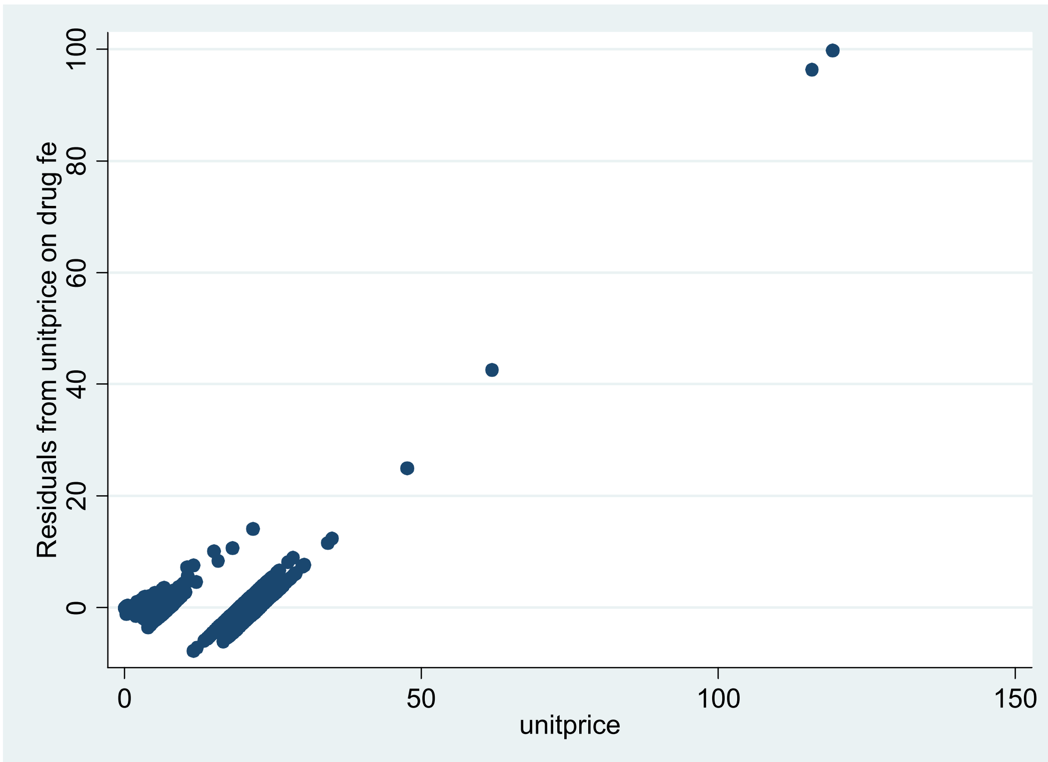


Figure A.2: Residuals from Drug Fixed Effects on the LN(Unit price)

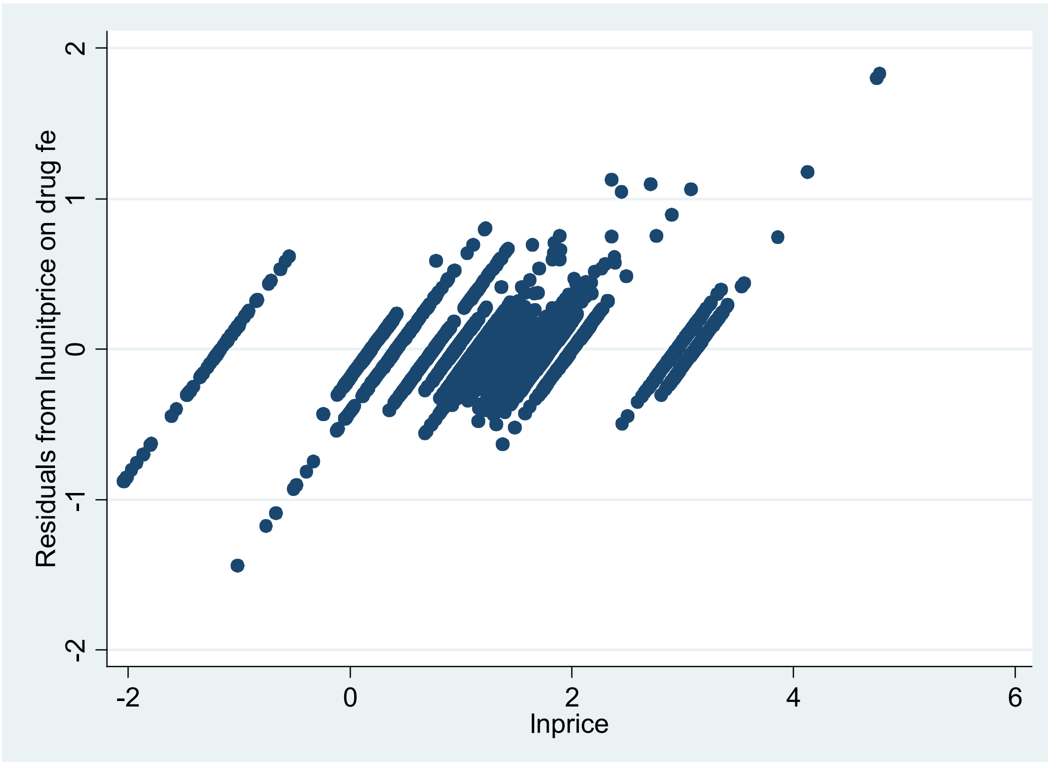
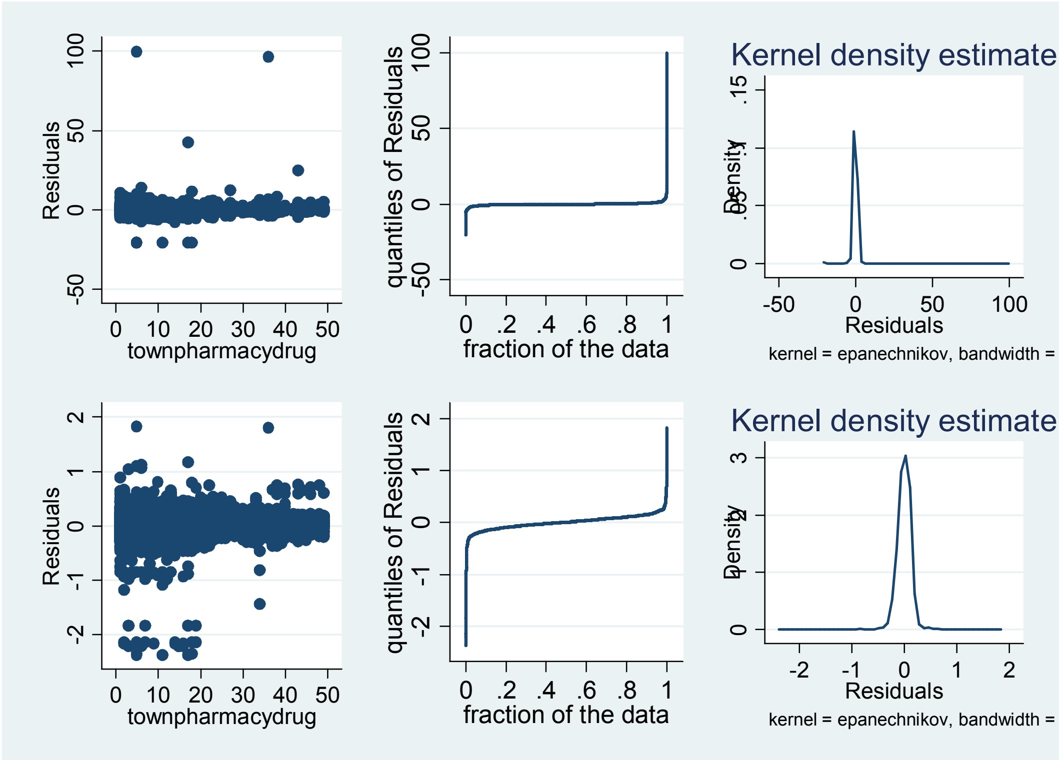


Figure A.3: Residual diagnostics for price levels



Top Left Panel – Scatter plot of residuals from regression of the unit price on drug fixed effects on y axis, and on the x-axis, the number of pharmacies in each town

Top Middle Panel – Quantile Plot of residuals shows larger errors for higher values

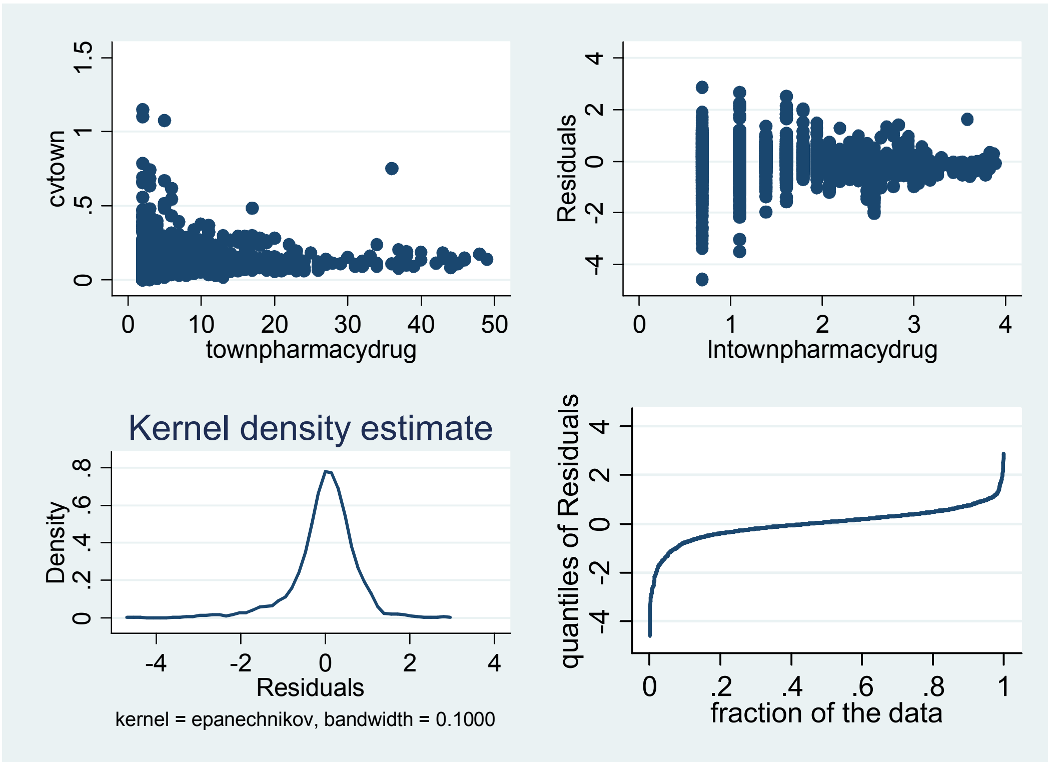
Top Right Panel – A kernel density plot shows that the distribution of the residuals are skewed to the right

Bottom Left Panel – Scatter plot of residuals from regression of the natural log of unit price on drug fixed effects on y axis, and on the x-axis, the number of pharmacies in each town

Top Middle Panel – Quantile Plot of residuals shows a much more symmetrical distribution

Top Right Panel – A kernel density plot shows the same thing as the quantile plot

Figure A.4: Residual diagnostics for price dispersion



Top Left Panel – Scatter plot of coefficient of variation of drug prices (on y axis) against number of pharmacies in each town that sold the drug (on x axis). These measures of CV are at the town level.
Top Right Panel – Scatter plot of residuals from log linear model. Residuals from regression of the natural log of the coefficient of variation of price on drug fixed effects on y axis and the natural log of number of pharmacies in each town on the x-axis.
Bottom Left Panel - A kernel density plot shows that the distribution of the residuals from the semi-log model are somewhat skewed to the left
Bottom Right Panel – A quantile plot showing larger errors for lower values of residuals from

Bibliography

Akerlof, George A. (1970). "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism". Quarterly Journal of Economics (The MIT Press) 84 (3): 488–500.

Alba, Joseph, John Lynch, Barton Weitz, Chris Janiszewski, Richard Lutz, Alan Sawyer and Stacy Wood, “Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces,” Journal of Marketing, 61(July), pp. 38-53, 1997.

Anand, Bharat and Ron Schacher, "Brands: Information and Loyalty," Working Paper, Harvard Business School, 2000.

Anania, Giovanni and Rosanna Nistico, “Public Regulation as a Substitute for Trust in Quality Food Markets,” Journal of Institutional and Theoretical Economics, JITE 160, 2004, 681-701.

Arbatskaya, Maria, "Ordered Reservation-Price Search and Equilibrium Price Dispersion," Working Paper, August 2000.

Arbia, Giuseppe, Michele Batistis and Gianfranco Di Vaio, “Institutions and geography: Empirical test of spatial growth models for European regions,” Economic Modeling, Volume 27, Issue 1, January 2010, pages 12-21.

Ariely, Dan and John Lynch, "Wine Online: Search Costs and Competition on Price, Quality and Distribution," Working Paper, 2001.

Aronson, Thomas, Mats Bergman and Niklas Rudholm, "The Impact of Generic Drug Competition on Brand Name Market Shares - Evidence from Micro Data," Review of Industrial Organization, 425-435, 2001.

Austin, Andrew and Jane Gravell, “Does Price Transparency Improve Market Efficiency? Implications of Empirical Evidence in Other Markets for the Health Sector,” CRS Report for Congress, April, 2008

Bailey, Joseph P, “Intermediation and Electronic Markets: Aggregation and Pricing in Internet Commerce,” PhD. Thesis, MIT, 1998.

Baye, Michael R., and John Morgan , "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets," American Economic Review, pp. 454-474, June 2001.

Baye, Michael R., and John Morgan , "Information Gatekeepers and Price Discrimination on the Internet," Working Paper, July 2001.

Baye, Michael R., John Morgan and Patrick Scholten, "Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site," Working Paper, July 2001.

Baylis, Kathy & Perloff, Jeffrey M., "Price Dispersion on the Internet: Good Firms and Bad Firms," Institute for Research on Labor and Employment, Working Paper Series 324, Institute of Industrial Relations, UC Berkeley, 2002.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" Quarterly Journal of Economics, 19(1): 249–75.

Brown, Jeffrey and Austan Goolsbee, "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry," The Journal of Political Economy, June, 2002.

Brynjolfsson, Erik, and Michael D. Smith, "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," Working Paper, MIT, 1999.

Brynjolffson, Erik and Michael D. Smith, "The Great Equalizer? Consumer Choice Behavior at Internet Shopbots, " Working Paper, MIT, 2000

Burdett, Kenneth and Kenneth L. Judd, "Equilibrium Price Dispersion," Econometrica, Vol. 51, No. 4, pp. 955-970, July, 1983.

Buzzelli A, et al,"Impact of generic substitution on pharmaceuticals prices and expenditures in OECD countries," Journal of Pharmaceutical Finance, Economics and Policy, volume 15 (2006), p. 41–63.

Carlson, John and Preston McAfee, "Discrete Equilibrium Price Dispersion," The Journal of Political Economy, Volume 91, Issue 3, 480-493, June 1983.

Carlton, Dennis and Judith Chevalier, "Free Riding and Sales Strategies for the Internet," NBER Working Paper 8067, January 2001.

Cason, Timothy and Daniel Friedman, "Buyer Search and Price Dispersion: A Laboratory Study," Working Paper, January 2000.

Caves R. E., M.D. Whinston and M.A. Hurwitz, "Patent Expiration, Entry and Competition in the U.S. Pharmaceutical Industry," Brookings Papers on Economic Activity, Washington DC: Brookings Institution, 1991.

Chandra, Ambarish and Tappata, Mariano E., Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets (March 1, 2011). Available at SSRN: http://ssrn.com/abstract=1116054

Chen, Yuxin and K. Sudhir, "When Shopbots Meet Emails: Implications for Price Competitions on the Internet," Working Paper, 2001.

Cheng, June and Nault, Barrie R., Internet Channel Entry: Retail Coverage and Entry Cost Advantage (January 16, 2006). Available at SSRN: http://ssrn.com/abstract=889366

Choudhury Vivek, Kathleen S.Hartzel, and Benn R. Konsynki, “Uses and Consequences of Electronic Markets: An Empirical Investigation in the Aircraft Parts Industry,” MIS Quarterly, 22(4), pp. 471-508, 1998.

Clay, Karen, Ramayya Krishnan, and Eric Wolf, "Prices and Price Dispersion on the Web: Evidence from the Online Book Industry," Journal of Industrial Economics vol. 49, issue 4, pages 521-39, 2001.

Clay, Karen, Ramayya Krishnan, Eric Wolf and Danny Fernandes, "Retail Strategies on the Web: Price and Non-Price Competition in the Online Book Industry," The Journal of Industrial Economics, Volume L, 349-367, September 2002.

Clemens, Eric K., Horn Hann, and Lorin M.Hitt, “The Nature of Competition in Electronic Markets: An Empirical Investigation of Online Travel Agent Offerings,” Working Paper, Wharton School, PA, 2000.

Cortese, Amy E. and Marcia Stepanek, “Good-Bye to Fixed Pricing? How Electronic Commerce could Create the Most Efficient Market of them All,” Business Week, pp. 71-84, May 4, 1998.

Costello, Anna, "The Impact of the Reference Price System on the Spanish Pharmaceutical Market: A Theoretical Approach," Working Paper, February 2000.

Danzon, P.M. and M. Furukawa, “Prices and Availability of Pharmaceuticals: Evidence from Nine Countries,” Health Affairs, July 2004.

Degeratu, Alexandru, Arvind Rangaswamy, and Jianan Wu, “Consumer Choice Behavior in Online and Traditional Supermarkets: The Effects of Brand Name, Price and Other Search Attributes,” Working paper, Penn State University, 1999.

Ellison, Glenn and Sara Fisher Ellison, “Search, Obfuscation, and Price Elasticities on the Internet,” Working Paper, MIT, 2006.

Familes USA, "No Bargain: Medicare Drug Plans Deliver High Prices," January, 2007

Fishman, Arthur, "Search Technology, Staggered Price-Setting and Price Dispersion," The American Economic Review, Volume 82, Issue 1, pp. 287-298, March 1992.

Gatti, J. Rupert, J. and Kattuman, P. (2003) "Online price dispersion within and between seven European countries." In Baye, M.R. (ed.): Advances in applied microeconomics: vol.12: organizing the new industrial economy. London: JAI Press, pp.107-141
Gencarelli D, "Average wholesale price for prescription drugs: is there a more appropriate pricing mechanism?" NHPF Issue Brief. 2002 Jun 7;(775):1-19

Goldmanis, Maris, Ali Hortacsu & Chad Syverson & Onsel Emre, 2008. "E-commerce and the Market Structure of Retail Industries," NBER Working Papers 14166, National Bureau of Economic Research, Inc

Grabowski, H.G. and J.M. Vernon, "Brand Loyalty, Entry, and Price of Pharmaceuticals After the 1984 Drug Act," Journal of Law and Economics, Vol 35, 1992.

Greenwald, Amy and Jeffrey Kephart, "Shopbots and Pricebots," IBM Institute for Advanced Commerce, published in proceedings of IJCAI, 1999

Hong, Han and Mathew Shum, “Using Price Dispersion to Estimate Search Costs," The Rand Journal of Economics. Vol 37 No 2 (Summer 2006) 257-275.

Hotelling, Harold (1929), "Stability in Competition", Economic Journal 39 (153): 41–57.

Janssen, Maarten and Rob van der Noll, "Electronic Commerce and Retail Channel Substitution," Working Paper, Timbergen Institute, April 2002.

Kauffman, Robert and Charles Wood, "Follow the Leader? Strategic Pricing in E-Commerce," Working Paper, University of Minnesota, November 2000.

Kauffman, Robert and Charles Wood, "Analyzing Competition and Collusion Strategies in Electronic Marketplaces with Information Asymmetry," Working Paper, University of Minnesota, 2001.

Keller, Godfrey and Sven Rady, "Price Dispersion and Learning in a Dynamic Differentiated-Goods Duopoly," Center for Economic Policy Research Discussion Paper No. 2919, August 2001.

Lal, Rajiv and Miklos Sarvary, "When and How is the Internet Likely to Decrease Price Competition," Marketing Science, Vol. 18, No. 4, pp. 485-503, 1999.

Lehmann, Erik, "Pricing Behaviour on the Web: Evidence from Online Travel Agencies," German Economic Association of Business Administration Discussion Paper No. 01-20, 2001.

Levinson, Daniel R, "Medicaid Drug Price Comparison: Average Sale Price to Average Wholesale Price," Office of Inspector General, Department of Health and Human Services, 2005.

Macminn, Richard, "Search and Market Equilibrium," The Journal of Political Economy, Volume 88, Issue 2, April 1980, 308-327.

McCall, John, "Economics of information and job search," Quarterly Journal of Economics 84 (1): 113–126, 1970.

Medicare Fact Sheet, Kaiser Family Foundation, January, 2010

Milgrom, Paul and John Roberts, “Price and Advertising Signals of Product Quality,” The Journal of Political Economy, Vol. 94, No. 4. pp.796-821, August 1986.

Morgan, John and Martin Sefton, "Information Externalities in a Model of Sales," Economic Bulletin, Vol. 4, No. 7, pp. 1-5, 2001.

Nelson, Rand, Richard Cohen and Frederik Rasmussen,"An Analysis of Pricing Strategy and Price Dispersion on the Internet" Eastern Economic Journal, 2007, vol. 33, issue 1, pages 95-110

New York Times, December 3, 2008

Pan, Xing, Brian Ratchford and Venkatesh Shankar, "Why Aren't Prices of the Same Item the Same at Me.com and You.com?: Drivers of Price Dispersion Among E-Tailers," Working paper, 2002.

Png, Ivan, Tom Lee and Cui Yan, "The Competitiveness of On-line vis-à-vis Conventional Retailing," Working Paper, National University of Singapore, 2000.

Reinganum, Jennifer F., "A Simple Model of Equilibrium Price Dispersion," The Journal of Political Economy, Vol. 87, No. 4., pp. 851-858, August, 1979.

Rey, S., & Montouri, B. (1999). US Regional Income Convergence: A Spatial Econometric Perspective. Regional Studies, 33(2), 143-156. Routledge.

Ronchetti, E. "Robust model selection in regression," Statistics & Probability Letters 3, 21-23, 1985

Salop, Steven C., "Strategic Entry Deterrence," The American Economic Review, Vol. 69, No. 2, pp. 335-338, May, 1979.

Salop, Steven and Joseph Stiglitz, "Bargains and Ripoffs: A Model of Monopolistically Competitive Price Dispersion," The Review of Economic Studies, Vol. 44, No. 3, pp. 493-510, October, 1977.

Scott Morton, Fiona, Florian Zettelmeyer and Jorge Silva Risso, "Internet Car Retailing," NBER Working Paper 7961, 2001.

Smith, Michael and Erik Brynjolfsson, "Consumer Decision Making at an Internet Shopbot," Quarterly Journal of Economics (forthcoming), 2001.

Sorensen, Alan, "Equilibrium Price Dispersion in Retail Markets for Prescription Drugs," Journal of Political Economy, 108(4): 833-850, 2000.

Sorensen, Alan, "Price Dispersion and Heterogeneous Consumer Search for Retail Prescription Drugs," Working Paper, January 2001.

Srinivasan, Narasimhan and Brian T.Ratchford, "An Empirical Test of a Model of External Search for Automobiles," Journal of Consumer Research, pp. 233-242, 1991.

Stahl, Dale, "Oligopolistic Pricing with Sequential Consumer Search," The American Economic Review, Volume 79, Issue 4, pp. 700-712, 1989.

Stigler, George, "The Economics of Information," Journal of Political Economy, 69(3), pp. 213-225, 1961.

Varian, Hal,"A Model of Sales," American Economic Review, American Economic Association, vol. 70(4), pages 651-59, September, 1980.

Web21 at http://www.web21.com, 2000.

Wooldridge, Jeffrey M., "Econometric analysis of cross section and panel data," Cambridge, MA: MIT Press, 2002

Zettelmeyer, Florian, Fiona Scott Morton and Jorge Silvo Risso, "Cowboys or Cowards: Why are Internet Car Prices Lower?" Working Paper, October 2001.

Zettelmeyer, Florian, Fiona Scott Morton and Jorge Silva-Risso, "How the Internet Lowers Prices: Evidence from Matched Survey and Auto Transaction Data," Journal of Marketing Research, 43(2), 2006: 168-181

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Southern Economics Association