DRUG PRICE CONTROL POLICY AND ACCESS TO MALARIAL DRUGS IN INDIA

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This dissertation investigates the effects of a drug price control policy implemented in India on consumer welfare. Methodologically this relates to estimation of endogenous product choice game of multi-product firms in a static framework. It builds on the existing literature on price control policy and literature on endogenous product choice and seeks to make two contributions. First, through empirical analysis, it demonstrates that not all price controls are equal. In fact, some price control policies could actually hurt consumers relative to the situation with no price controls. This is because, while price controls lower prices and make pharmaceutical products more affordable, they might backfire if firms respond to these policies by withdrawing from the market, which would result in reduced access. On one hand, unregulated prices, if too high, preclude most consumers from purchasing these drugs. On the other hand, regulated prices, if too low, result in few products being offered on the market. Second, it builds on the Moment inequality literature, and proposes a solution to a selection problem that arises while estimating cost parameters using (observed) firms' endogenous choices of product portfolio.

In this analysis, we focus on drugs that cure malaria, an important neglected disease in the context of the Indian pharmaceutical market. We use a novel and unique dataset which features detailed region level sales and price data. We exploit the significant demographic heterogeneity across different regions in India

to estimate a two stage game, where firms endogenously make product entry and exit decisions across different markets as well as fix prices of the offered products. The richness of the model requires us to confront econometric challenges associated with multiplicity of equilibria, endogeneity, and inference in partially identified models, as well as computational challenges associated with the high dimensionality of the problem. Our estimation results show that there is substantial variation in demand elasticities and willingness-to-pay across different regions in India, and that firms incur significant fixed costs for making the developed drugs available in the local markets. Moreover, fixed costs are heterogeneous across firms and across regions. The results of our counterfactual analysis show that under price control, small domestic firms and foreign firms withdraw their products, and markets become more concentrated. In most cases, only the big-domestic firms continue producing the drugs. Depending on the level of price control, the loss in consumer welfare due to products withdrawal may exceed the gain in consumer welfare resulting from lower prices, leading to an overall decrease in consumer welfare.

BIOGRAPHICAL SKETCH

Debi Prasad Mohapatra joined the PhD program in Economics at Cornell University in the Fall of 2010. He obtained his Bachelor of Arts degree in Economics from B.J.B.(Autonomous) College, Odisha in 2007 and Master of Science in Quantitative Economics degree from Indian Statistical Institute, Kolkata in 2009. Beginning Fall, 2016, he will be joining University of Massachusetts Amherst as a Tenure-Track Faculty in the Department of Resource Economics.

To my Mother, for teaching the most valuable lessons in life

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CHAPTER 1

INTRODUCTION

Governments in developing and underdeveloped countries adopt drug price control policies to ensure that essential medicines are available to consumers at reasonable prices[1] and consumer welfare is maximized. However, those policies can have ambiguous effects when it comes to achieving such goals. Lower prices make drugs more *affordable*, thereby increasing access to the drugs and consumer welfare. On the other hand, price control may disincentivize firms from making the drugs *available* in local markets, thereby decreasing access to drugs and consumer welfare. As such, the effect of price control on access to drugs and consumer welfare is a question that calls for empirical investigation. Because the majority of consumers in these countries do not have health insurance, and health care expenses have to be paid out-of-pocket, the welfare implications of these policies are even more significant.

In this paper, we evaluate the effect of a price control policy on access to drugs and consumer welfare while accounting for firms' incentives to adjust their product portfolio in the market. Our analysis is done in the context of malarial drugs in the Indian pharmaceutical industry. We use a new and unique dataset that records sales and prices of drugs sold across 23 different regions in India on a monthly frequency from 2007 to 2013.

Using this dataset, we estimate a model of supply and demand where both the set of products offered in the market by a firm and their prices are endogenously determined. Regional disaggregation of our dataset provides us with a unique advantage over most of the existing studies on the Indian pharmaceu-

[1] Throughout the paper we refer to this as access to drugs.

tical industry, since we use the significant variation across different regions to estimate our model. We model a two-stage game played by the drug manufacturers: in the first stage firms face a discrete menu of molecules and simultaneously choose which set of products to offer in each region. In the second stage, the chosen products are sold to the consumers in a simultaneous-price-setting game. While consumer heterogeneity and profitability provide incentives to firms to offer multiple products in a region, offering each of these products results in fixed costs. In our empirical investigation, we therefore need to estimate both expected variable profit and fixed costs.

To learn expected variable profit, we estimate a random coefficient logit model to recover the distribution of consumer preferences following Berry, Levinsohn, and Pakes [1995, BLP, hereafter]. We recover marginal costs for drug production using equilibrium first-order conditions resulting from firms' profit maximization. To learn total fixed cost, we use a revealed preference argument commonly used in empirical entry literature, specifically, the fact that, a firm offers a product only if its variable profit exceeds the corresponding fixed cost. Naturally, this condition yields a selected sample of offered products, and we address the associated endogeneity problem ("selection problem" as discussed in Pakes, Porter, Ho, and Ishii [2015, PPHI, hereafter]) by proposing a novel instrument that exploits the region-level variation in our data.

Our estimates reveal the presence of heterogeneity across different regions in terms of demand characteristics such as elasticities and willingness to pay. Consumers in high-income regions are on average less price sensitive compared to consumers in low-income regions. In addition, our estimates indicate that fixed costs are a significant proportion of variable profit and vary across regions and

across firms. In low-income regions, firms face higher fixed costs on average compared to high-income regions. Fixed costs of big-domestic firms as a fraction of variable profit are generally smaller compared to small-domestic firms and foreign firms. The small-domestic firms operate with low margins and in fewer regional markets.

We then perform counterfactual analyses to evaluate the impact of price control on access to drugs and consumer welfare. We fix the markup on the marginal cost at a given level, allow firms to adjust the set of products, and examine whether consumer welfare increases with price control. For each firm, we fix prices by allowing markup at different levels (8% and 15%) and we simulate the firm's product entry decisions across different regions.

Our analysis reveals that, first, fixed costs are large enough to induce exit of products from the market. As we decrease the margins from 15% to 8%, firms across all regions withdraw their products. Second, in high-income regions, however, product withdrawal is less prominent compared to low-income regions. In low-income regions, fewer firms operate even with 15% margin. Hence, with a further reduction in margin, firms withdraw their products. In some regions, all firms withdraw all products of a molecule resulting in no access to that specific molecule. Third, because big-domestic firms face lower fixed costs across regions, they continue to offer their products in most regions, even under lower margins. In low-income regions, when the margins are lower, only the big-domestic firms would operate, leading to an increase in market concentration. In addition, given price control and product withdrawal, our calculations show that the total consumer welfare with 8% price control is lower compared to the 15% price control. Our framework makes it possible to elicit

these findings since it combines a study of endogenous product portfolio and prices with a detailed analysis of cost and demand.[2]

We focus on drugs that cure malaria in the context of the Indian pharmaceutical industry. Malaria is an important neglected disease with a very high disease burden[3] in India (see Kumar, Valecha, Jain, and Dash [2007]). It is widely reported that the parasite causing malaria is mostly resistant to older and relatively cheaper drugs. New and more effective drugs are however relatively highly priced. Moreover, efficacy and suitability of the drugs vary across consumers depending on age, gender, and health condition. Hence, to fight this disease, multiple antimalarial therapies are widely recommended.

It is worth pointing out that access to drugs not only depends on firms' incentives for drug availability (making the drug available in local markets) and drug affordability (drugs to be reasonably priced), but also on firms' incentives to develop the drug (R & D). However, the research and development of malarial drugs is primarily funded by several international organization (like Medicines for Malaria Venture (MMV), Drugs for Neglected Diseases *initiative* (DNDi), Bill and Melinda Gates foundation). Once the drugs are developed, the marketing rights are provided to different firms. Hence, the access to drugs depends crucially on availability of the drug in the local markets and affordability of the drug.

The regional markets in India differ significantly from each other in terms of demographic characteristics, including per capita income, age distribution, and knowledge and training of the local doctors. In addition, health infrastructure

[2]It is worth pointing out that we extensively consulted with regulators as well as officials from different firms in India to ensure plausibility of our results.

[3]Disease burden is a measure that combines years of life lost due to premature mortality and years of life lost due to time lived in states of less than full health (WHO)

facilities such as access to doctors and drug stores, availability of drug storage, transportation facilities and distribution infrastructure also vary across regions. This leads to variation in terms of firm profitability across regions. Since firms charge the same price for a drug across all regions, firms may continue to offer or withdraw their products in response to a policy change, depending on the level of price control, profitability of the region and level of fixed cost faced by the firm in the region.

Methodology

The model in this article has the following key features: (i) It allows firms to make multiple discrete-product choices, so that both the number and identity of offered product are treated as endogenous. (ii) It incorporates a detailed model of differentiated-product cost and demand system. (iii) It allows for firm-region-product specific structural errors, and proposes a new way to deal with the resulting endogeneity bias issues. The estimation methods used in this article belong to a growing literature on endogenous product choice (e.g. Eizenberg [2014], Nosko [2011], Wollmann [2014]; see Crawford [2012] for a recent survey).

In our model of product entry, we assume complete information and employ Subgame Perfect Nash Equilibrium as solution concept. As it is well established in the entry literature (e.g. Tamer [2003]), uniqueness of equilibrium is not guaranteed, leading to partial identification of fixed costs (Andrews, Berry, and Jia [2004], Ciliberto and Tamer [2009], Beresteanu, Molchanov, and Molinari [2011]). We exploit the necessary equilibrium conditions to place bounds on partially identified parameters following PPHI, and Ho and Pakes [2013]. Most of the applications in entry literature employ a reduced-form profit function, whereas we derive the profit function from micro-foundations with a detailed

model of cost and demand. We use techniques recently developed in Kaido, Molinari, and Stoye [2015], to obtain element-wise confidence intervals on the fixed cost parameters that are asymptotically uniformly valid.

A sample selection problem arises in the entry model, as firms are explicitly assumed to have selected the set of products observed in the data. Such selection problems are extensively discussed in PPHI and Eizenberg [2014], and several possible solutions are proposed in these papers. In our framework, however, these standard solutions are not directly applicable. Since our structural errors in the entry stage are product specific, the errors can not be differenced out as suggested by PPHI. We therefore propose a novel solution, which exploits the regional variations in our data to construct monotone instruments to address the selection problem. The idea of monotone instruments was first proposed in Manski and Pepper [2000] and further discussed in PPHI. The intuition behind our proposal is straightforward: firms face similar fixed costs in regions with similar demographic characteristics and infrastructure facilities, hence we can use observable determinants of entry in one region, to predict entry in "similar" regions. Using this idea, we construct monotone instruments that can plausibly solve the selection problem.

Finally, this article contributes to a growing literature on the effect of price control and government policy-related topics in the context of developing countries. (e.g. See Goldberg [2010], Duggan, Garthwaite, and Goyal [2014], Kyle and Qian [2014], Kyle and McGahan [2012], Kyle [2007], Bond and Saggi [2014], Filson [2012], Kessler, Lanjouw [1998], Lanjouw [2005], Lanjouw [1998], Branstetter, Chatterjee, and Higgins [2011], Branstetter, Chatterjee, and Higgins [2014], Chatterjee, Kubo, and Pingali [2015]). Through theoretical mod-

els and reduced form studies relying on cross-country observations, these papers clearly demonstrate the inherent trade-offs faced by Government policies, in the context of India as well as many other countries. We add to this literature by providing a detailed structural analysis of consumer heterogeneity, and firm behavior, and by studying the effects of policies to maximize consumer welfare. In closely related work, Chaudhuri, Goldberg, and Jia [2006] study the Quilonole antibiotic segment in India, and investigate the welfare implications of patent policy while allowing firms to adjust prices. Dutta [2011] also addresses welfare implications of patent policy by allowing firms to respond to policy changes, while treating all firms as homogeneous single product units. In contrast, we use regionally disaggregated data, allow full heterogeneity across firms and regions, and study the welfare implications of a policy change while allowing firms to readjust both product offerings and prices in response to the policy change.

The rest of the article is organized as follows: Section 2 describes industry and the data. Section 3 presents the model. Section 4 discusses identification and estimation. Section 5 discusses the results from our estimation. Section 6 reports results from counterfactual analysis. Section 7 concludes.

1.1 Industry Background and Data

1.1.1 Malaria in India

Malaria is a mosquito-borne infectious disease of humans and other animals, caused by parasitic protozoans (a type of single cell microorganism) of the Plasmodium type. According to US Center for Disease Control, more than 90%

of the malaria cases in India is due to two strains of the parasite, P. vivax, P. falciparum. According to the National Vector Borne Disease Control Program (NVBDCP), of the reported cases in India in 2012, 50.01% are due to P. falciparum. Malaria caused by P. falciparum species is the most dangerous form of malaria, with the highest rates of complications and mortality. Although infection due to P. vivax is not life threating, yet it does cause serious damage to the body and worsens health significantly.

Most strains of malaria are traditionally treated with chloroquine which is a cheaply and widely available molecule across different countries. However, P. falciparum and increasingly P. vivax have developed resistance to this treatment. Recently more effective (and also more costly) artemisinin-based combination therapies (ACTs) are developed to cure malaria with resistance.

Malaria imposes a great socio-economic burden on humanity, and with six other diseases (diarrhea, HIV/AIDS, tuberculosis, measles, hepatitis B, and pneumonia), accounts for 85% of the global infectious disease burden.[4] Malaria is specific to least developed and developing Asian and African countries and mostly rare in developed countries. In the Southeastern Asian Region of WHO, out of 1.4 billion people living in 11 countries (land area, 8,466,600 km^2, 6% of global area), 1.2 billion are exposed to the risk of malaria, most of whom live in India. India alone contributes close to 76% of the total malaria cases reported in South-East Asia. Most of the malaria burden is borne by economically productive ages. Taking into account lost earnings due to bad health, as well as treatment costs, apart from mortality, malaria imposes a huge economic burden in India. [5]

[4]Reference: Kumar, Valecha, Jain, and Dash [2007], Gupta and Chowdhury
[5]Gupta and Chowdhury calculates the burden to be US$ 1940 million

However, the commercial market for new drugs to treat or prevent malaria is insignificant, because people affected by these diseases have negligible purchasing power. The small size of this market means that private sector investment in R& D is also small. Given lack of incentives for conducting costly and risky research and development, R & D is mostly conducted by non-profit organizations like Drugs for Neglected Diseases initiative (DNDi) and Medicines for Malaria Venture (MMV). These organizations generally raise funds from different foundations (like Bill and Melinda Gates foundation) and work with a commercial partner through all the phases of the drug research and development (R& D) pipeline, from early discovery, through development and regulatory approvals, to delivery of the drug to the market. The intellectual property right of the developed drug is generally retained by these organizations and marketing rights are provided to firms to make sure the distribution of drugs across different countries.[6]

It is important to point out that different malarial molecules are not perfect substitutes of each other. A molecule can be especially suited for specific age or type of patient, but not for other group of patients. For example, treating children and pregnant women suffering from malaria is a lot more complex than treating the average adult patient, since these two groups are the most vulnerable. They require medicines tailored to their needs with robust safety profiles and drugs need to be carefully administered for these two groups. That apart since drug resistance is an important challenge in treating malaria, from purely physiological point of view, multiple first line of treatments can be important to delay the commencement of resistance. Several drug regimen strategies can be applied to maximize the lifespan of the currently used antimalarials. (see

[6] see the intellectual property policy of MMV for more details (Link)

Petersen, Eastman, and Lanzer [2011], Boni, Smith, and Laxminarayan [2008] for a discussion on multiple treatments). The WHO technical advisory group, while meeting in India in 2004, also recommended the use of multiple combination antimalarial therapy, particularly with artemisinin derivatives to delay the emergence of drug resistance. (see Anvikar, Arora, Sonal, Mishra, Shahi, Savargaonkar, Kumar, Shah, and Valecha [2014]).

1.1.2 Price Control in India: 1995 and 2013

Price control is one of the key instruments Indian Government has used with a goal to ensure availability of drugs at affordable prices. This is especially used extensively after India ratified patent protection by adopting TRIPs. Under TRIPs agreement, Indian government has reserved few flexibilities like price control and compulsory licensing so as to make sure drugs are available in the local market at a reasonable price. However, compulsory licensing is used rarely by different countries making price control as one of the key tools in the hand of the Government. For example, in 2013, the Indian government has published the Drug (Price Control) Order (DPCO) 2013, bringing 652 drugs under price control, representing around 30% of the pharmaceutical market.

Drug price control in India is guided by Drug price control order 1995 and Drug price control order 2013. According to DPCO 1995, the retail price of a formulation is calculated by the Government in accordance with the following formula:

$$\text{Retail Price} = (\text{Cost Estimate}) \times (1 + \text{margin}/100) + \text{excise duty}$$

where cost estimate would include material cost, packaging cost, and other

manufacturing costs. Typically, the margin here would be between 10% and 15% (see Dutta [2011]).

The price control rule got revised in 2013. As per DPCO 2013, Average Price to Retailer of the scheduled formulation is calculated using the rule: Average Price to Retailer,(P(s))= (Sum of prices to retailer of all the brands and generic versions of the medicine having market share more than or equal to one percent of the total market turnover on the basis of moving annual turnover of that medicine) / (Total number of such brands and generic versions of the medicine having market share more than or equal to one percent of total market turnover on the basis of moving annual turnover for that medicine.)

The ceiling price (P(c)) of the scheduled formulation is calculated using the formula: P(c) = P(s).(1+M/100), where P(s) = Average Price to Retailer for the same strength and dosage of the medicine as calculated in step1 above. M = % Margin to retailer. Typically the margin is fixed at 16%.

According to para 15 of DPCO 1995, each drug in India must display its price on the pack which is also referred to as maximum retail price. Typically, this is the price consumers have to pay while purchasing the drug. However, there may be discounts offered by some retailers. Typically, the manufacturers pay a fixed proportion of the price to the retailer and the rest goes to the manufacturer.

For our counterfactual exercise, we will follow the setting of DPCO 1995, we will fix the margin at different levels, ignore any discounts faced by the consumer and examine how firms would make product choices given price and expected variable profit.

1.1.3 Data: Source and Description

We obtained our data from the AIOCDs (All India Organization of Chemists and Druggists) subsidiary marketing research company AIOCD Awacs Pvt. Ltd. Founded in 2007, AIOCD Awacs collects rich data from monthly sample surveys of its membership, the stockists and retailers aligned with its association, which is estimated to be 95 percent of all traders in India. The AIOCD data are arguably more accurate relative to the IMS data, an alternative private source, as the AIOCD has better coverage and compliance among its members in reporting sales data. The AIOCD data are widely used by financial analysts as well as by Competition Commission of India for examination of its anti-trust cases. The data relate to 2580 medicines each with a unique active ingredient (or a unique combination of ingredients) that were sold in India between March 2007 and September 2013. Each ingredient or combination of ingredients is associated with a unique four-digit classification number under the European Pharmaceutical Marketing Research Association (EPhMRA). Our data are also disaggregated at the regional level among 23 geographic markets carved out by the AIOCD. It is worth pointing out that most of the current studies in Indian pharmaceutical Industry including Chaudhuri, Goldberg, and Jia [2006] and Dutta [2011] use price and sales data from IMS which divides India into four broad divisions[7]. The geographic disaggregation of AIOCD data provides us with an unique advantage over IMS data, as we use the significant variations across different regions in India to study the incentives of the firms to make the product *available* in different regional markets in India. Note that pharmaceutical products are available in multiple presentations, that is, combination of dosage forms (e.g. capsules, tablet and syrup), strength (e.g. 100 milligrams,

[7]IMS data divides India into North, South, East and West

500 milligrams) and packet sizes (e.g. 50 capsule bottle, 100 tablet bottle). The various presentations in which a product is available are often referred to as stock-keeping-units (SKUs). The data are organized monthly and contain information on firm-level sales and quantity sold at the stock keeping unit (SKU) level, which is more disaggregated than the EPhMRA-level. The data also contain maximum retail price (MRP) at the SKU level and distinguishes medicines into chronic and acute categories based on their usage patterns.[8]

We focus our study on 11 molecules that are used to cure malaria. We also focus our attention on 21 out of 23 regions.[9] Indian government signed the TRIPs (Trade Related aspects of Intellectual Property Rights) agreement under the regime of WTO in 1995 and started patent protection for pharmaceutical products in 2005. In our sample, all these 11 molecules were released in India prior to 2005, hence none of these are under patent protection. Due to no patent protection, several domestic and foreign firms produce the molecule across different regions in India. Even if the same molecule (with same chemical composition) is produced by several firms in India, there is differentiation across these products, a point, which we will discuss in detail later. Graph A.1 plots the number of firms operating across different molecules. Chloroquine, pyrimehtamine+ sulphadoxine, and hydroxychloroquine are under price control since 1995. Due to low profitability, relatively less number of firms operate in these molecules.

Each firm sells these molecules in multiple presentations, also referred to as stock-keeping-units (SKUs). In our sample, we observe the sales and price data

[8] A recent study, Evans and Pollock [2015] has also used this dataset

[9] We drop two regions Delhi and West Uttar-Pradesh as most of the sales in West Uttar-Pradesh is registered in Delhi for tax purposes and it was hard to pin down the sales in these two regions separately.

at SKU level. However, we treat a *firm-molecule* pair as a product. For example, Chloroquine produced by two different firms: IPCA Laboratories and Zydus Cadilla are treated as two different products.

To get the product level variables, we combine the sales and prices of all the SKUs in a market for a given molecule produced by a firm. Since an SKU can be in liquid, solid or injection form, we consult pharmacological literature to convert the different presentations into number of dosages. For example, if one prescribed dosage involves two tablets each of 100 mg strength, then a 10 tablet pack would have 5 dosages in total. We also collect the information on the number of dosage for a complete treatment of a patient for each molecule. We refer to WHO model prescribing information (Organization et al. [1990]) and Hospital of the University of Pennsylvania Malaria Adult Treatment Guidelines (Link) for collecting this information. For example, 2500 mg of chloroquine over 3 days need to be administered per patient for a complete treatment with chloroquine. Generally Arteminisin derivatives need to be administered for shorter time periods and are more effective.

We convert the sales data for each SKU into number of patients and add across SKUs to get total sales for each molecule for a given firm. We obtain price per patient for each SKU by dividing price of each SKU with the number of complete dosages for the given SKU. We use sales share of each SKU as weights, and obtain the weighted average price by combining per dosage prices across different SKUs.

For a given SKU, its price across different regions is identical at a given point of time. There are time series variations in the price of a SKU over our sample period, but such variations tend to be infrequent and small in magnitude.

However, price charged by different firms for SKUs with identical pack size and strength information, tend to differ significantly. For example, the price of 60 mg injection of Artesunate varies between 73 Indian Rupees and 250 Indian rupees depending on the firm producing the SKU (Link). [10]

The degree of price variation is even more significant once we aggregate the SKUs to molecule level. Table A.1 lists the molecules and reports the average price per patient. For example, if a patient is detected positive for malaria, and chooses to consume mefloquine, then the patient on an average needs to pay 267 Indian rupees for a complete treatment. The third column in the table reports the number of patients in our entire sample that consumed the molecule. Out of these 11 molecules, three molecules, Pyrimethamine + Sulphadoxine, Chloroquine, and Hydroxychloroquine are under price control since 1995 (under Drug Price Control Order, 1995). Note that even though hydroxychloroquine is under price control, the average price is higher compared to other price controlled drugs. This is because, hydroxychloroquine is mostly available in injection form, and controlled price for injections is relatively higher compared to tablets and liquids.

Resistance of malaria parasite to Chloroquine and Pyrimethamine + Sulphadoxine has been widely reported across different regions in India.(See Gelband, Panosian, Arrow, et al. [2004] for a detailed study of economics of malaria). To counter resistance, WHO recommends to administer multiple therapies, by using the drugs developed from Arteminisn derivatives along with fixed dosage combinations. These new molecules are more effective for malaria treatment, but the average price is close to 20 times higher compared to the cheap drugs.

[10] We manually conducted external validation of prices at SKU level by consulting price data from websites CIMS India, and 1 mg.com

It is worth pointing out that average per capita monthly income of an individual under poverty line in India is close to 1100 Indian rupees, which means the prices of the new molecules pose significant financial burden for most of the patients with poor financial conditions.

The cheap drugs are more popular drugs and in our sample majority of the patients consume those drugs. Chloroquine is the most popular drug followed by Pyrimethamine + Sulphadoxine. Number of patients consuming new and more effective molecules is relatively lower.

Table A.3 shows the variation in number of malaria patients across different regions. Malaria cases are reported across all geographical regions in India. Highest number of cases are reported in Odisha, a low-income-region in India. In our sample, there are 85 different firms selling malarial drugs across different regions. Many of these firms are small local firms and operate only in few regions. In our data, in no region, more than around 20 firms sell malarial drugs. Figure A.4 shows the number of firms that are active across different regions. In this graph, an active firm is a firm that sells at least *one* molecule in the region. The variation in profitability across regions is apparent from the graph. Relatively higher number of firms operate in more profitable regions like Gujurat, Madhya Pradesh, Vidarbha and Mumbai. Firms not only differ in number, but also differ in offering product varieties for each molecule across different regions depending on the profitability of the regions. For example, in a region like Gujurat, an economically advanced region, firms tend to release more SKUs compared to an economically backward region like Bihar. These region level variations play important role in our analysis. We will use the variation in profitability across regions and revealed choices of the firms in offering products

across regions to infer bounds on the fixed costs.

Broadly, firms selling these drugs are divided into two categories: branded generic firms and small generic firms. Most of the big domestic firms sell the generic drug under some brand name, but the small generic firms sell the drug under the generic molecule name. Table A.2 lists all the 11 molecules and price spread across each molecule in our sample. The price spread in price controlled molecules come from two sources: a part of the variation is from time series variation, as price controlled molecules are allowed to revise their price by a fixed percentage over time to take into account the rising cost of production. Other part of the price variation is is due to the grouping of SKUs as, per dosage injections are priced higher compared to per dosage tablets and combining tablets with injections mechanically increases the per patient price of the molecule. Price variation for the molecules that are not under price control, is striking. Although a part of it is driven by grouping of SKUs, the significant variation across products with same chemical composition produced by different firms is a key contributing factor for the price variation.

In malaria, three firms, IPCA laboratories limited, Zydus Cadilla and Shreya Laboratories limited are top three firms in India. The level of market concentration varies across different regions in India and also over time. To highlight this variation, we report the the herfindhal index[11] across different regions in table A.3. The second column shows the average herfindhal index across regions. The level of concentration varies significantly (from 20.79 to 69.61). In regions like Gujarat and Mumbai, market concentration is much lower compared to North east and Jharkhand. Also, note that there is significant time-series varia-

[11]Herfindhal index a commonly accepted measure of market concentration. It is calculated by squaring the market share of each firm competing in a market, multiplying it with 100 and then summing the resulting numbers

tion across regions in terms of market concentration. For example, a region like North east has become much more concentrated over time (Herfindhal index in 2008 is 22.03 and in 2013, it is 89.92). Except for West Bengal Rest in all other regions, market concentration has increased over time.

From these descriptive statistics, we broadly infer two conclusions: There is significant regional variation in terms of number of number of firms and level of concentration across different regions in India. Also, firms are actively adjusting product portfolio across regions over time leading to significant time series variations. This is instrumental in identifying the cost of offering the products across different regions by different firms.

We now discuss the issues related to differentiation in pharmaceutical products. In India, although the same generic product is produced by different firms, we divide the products into branded generics and non-branded generics. If we follow commonly accepted definitions, Indian malarial market does not have branded medicines (a name commonly given to an innovator product). What we refer as branded generic products in India, are the products produced by big domestic firms which are sold under a brand name. They charge higher prices for the same SKU compared to the products which are sold under generic molecule name. We extensively talked to several firms to understand the differences among these products. We realized that branded generic products tend to maintain (or at least perceived to maintain) a higher quality compared to non-branded generic products. Hence, although the generic medicines are bioequivalents of their branded counterparts and are produced in similar facilities according to good manufacturing practices, these are widely believed as inferior in their therapeutic efficacy and quality compared to branded products.

This point is also highlighted in Shrank, Cox, Fischer, Mehta, and Choudhry [2009], and Basak and Sathyanarayana [2012]. We now discuss our definition of market, market size and use of other data sources to facilitate our estimation.

Definition of Market, market size and other data sources: Figure A.2 shows the total sales across different quarters. Sales in third and fourth quarter are consistently higher compared to first and second quarter over the entire sample period. Note that, seasonality in sales is expected, as mosquitoes, the vectors for malarial parasites, are more prevalent in rainy and monsoon seasons compared to winter season. This seasonality guides the definition of market in our demand analysis, and we treat a region-quarter combination as a market.

However, while estimating fixed cost of entry, allowing the firms to make product choice decisions, we take into account region-year as a market, that is we estimate average annual per product fixed cost for a firm in a given region. This is primarily guided by the average life of a drug. A drug can be typically consumed within a year of its manufacturing. After a year, it reaches its expiry date. Hence, we expect a firm to decide annually whether to offer the molecule in a region and hence treat region-year as a market while making product offer decision.

We refer to a website Indiastat.com and collect information on number of malarial patients reported across different regions in India. We construct market size using this information.

Apart from AIOCD data, we refer to consumption expenditure survey data collected by National Sample Survey Organization (NSSO) India to get the data

on demographics. In our random coefficient logit model, demographic information plays crucial role in explaining substitution patterns. We randomly select 1000 individuals from each region and collect their information on age, monthly per-capita expenditure and whether they belong to rural area or urban area in the specific region. Age plays a crucial role in malaria treatment. Children are especially vulnerable for malaria, however treatment is more complicated as children can intake drug only in liquid form. We observe per capita monthly expenditure data and it varies significantly across regions. In some regions like Odisha, there are majority of individuals who belong to rural area and in regions like Gujurat, higher number of individuals belong to urban area.

It is worth mentioning that our data comes from stockists and traders. Government of India under different flagship programs and under national rural health mission, distributes free malarial drugs through local primary health centers. Our data does not account for those drugs. In our analysis, drugs provided by Government is treated as an outside option for the patient. However, it is widely reported that the health centers run by Government in most cases does not have enough drugs in its reserve and people mostly rely on private sources to have access to malarial drugs.

Product offering and Fixed costs

We consider 11 different products. Not all products are produced by all firms and offered in all the regions. These molecules are available in different forms and the efficacy of the molecules also vary across the spectrum of patients.

Potential firm in a region: We include a firm in the set of potential firm in a region, if the firm has operated in that region at any point in our sample.

Big domestic firms like IPCA Pharmaceutical, Zydus cadilla operate in most of the regions in India. Hence, we consider these big firms as potential entrants into all the regions in India. However, there are many small generic firms that operate in specific regions. Among those small firms, we consider a firm to be a potential entrant in a region only if it has operated in the specific region at some time period in our sample.

Potential products for a firm: We consider 11 molecules that cure malaria. However, not all firms produce all the 11 molecules. For selling a drug in India, a firm needs to get an approval from the drug control authority in India. With this approval, a firm can potentially sell its products in any region in India. However, in our sample, we do not observe a firm selling all its molecule in all the regions. If a firm sells a molecule in some region of India, we include the molecule in the list of potential products for the firm. Note that this means, the set of potential products for a firm may differ from another firm, however a firm's menu of potential products remains same across all markets and all time periods.

Fixed costs: We assume that a firm incurs fixed cost while offering an additional product in the market. It is natural to ask why we should expect any substantial fixed costs. We extensively consulted people from industry and confirmed that the firms face significant costs for distribution and dispensing of the drugs across different regions in India. The distribution system consists of domestic and foreign manufacturers in the upstream, and large and small distributors (known as stockists and wholesalers) and retail traders in the downstream. In addition, large manufacturers appoint intermediaries (known as carrying and forwarding agents (CFA)) in each state of India to avoid federal sales tax on in-

terstate sale of goods. The downstream of the distribution system is organized into an association named "All India Association of Chemists and Druggists" (AIOCD). A manufacturer needs to get a "no objection certificate" from AIOCD to sell in a region. The distribution costs also include medicine acquisition, handling and delivery, packaging and labeling and insurance costs. Regional disparities in entry costs also arise due to different levels of infrastructure availability across different regions in India. Also, medicines expire in finite time period. Hence, stocks need to be regularly replenished. That apart, firms also spend significant amount in medical representatives to make the doctors aware about the efficacy of the drugs. It is worth pointing out that, fixed costs do not include direct-to-consumer advertising costs since, direct-to-consumer advertisements are not allowed in India[12].

Consistent with these ideas, we model fixed costs associated with offering a product in a region in a year allowing these costs to be subject to shocks at molecule-year level.

[12]USA and New-Zealand are the only two countries with direct-to-consumer advertisement of prescription drugs is allowed

CHAPTER 2

A MODEL OF ENDOGENOUS PRODUCT CHOICE IN OLIGOPOLY MARKET

2.1 Model

The primitives of the model are consumer demand for malarial drugs, marginal cost for producing the drug, fixed costs for releasing the drug in different local markets and the Subgame Perfect Nash Equilibrium (SPNE) concept of a game played by the oligopoly of the drug manufacturers. Next we describe the model in detail.

2.1.1 Demand

We follow BLP and model demand for drugs by a random-coefficient-logit specification. In a market a set of drugs, denoted by J_m are offered. A malarial patient chooses at most one of these products, or chooses the outside option of not purchasing any of them. The outside option in this framework would include treatment using traditional methods as well as treatment from public hospitals.

A consumer maximizes the indirect utility function. The utility derived by consumer i from consuming drug j in market m is given by

$$\begin{aligned} & u_{ijm}(x_{jm}, p_{jm}, \xi_{jm}, \nu_{im}, D_{im}; \theta^d) \\ & = \underbrace{x_{jm}\beta - \alpha p_{jm} + \xi_{jm}}_{\delta_{jm}} + \underbrace{[-\sigma\nu_{im}^p - \lambda D_{im}^p]p_{jm} + \sum_{k=1}^{K}[\sigma^k\nu_{im}^k + \lambda^k D_{im}^k]x_{jm}^k}_{\mu_{ijm}} + \varepsilon_{ijm} \end{aligned} \tag{2.1.1}$$

where x_{jm} is a K-vector characteristics of the drug j in market m observed by the econometrician. In our specification, this includes age of the molecule, number of SKUs offered by the firm in market m for the given molecule, number of years since the firm is active in the specific molecule, a measure of presence of firm in other close therapeutic categories[1], dummy variable for each product[2], region dummies and quarter dummies. The variable ξ_{jm} is a demand shifter unobservable by the econometrician. Price of drug j in market m is denoted by p_{jm}. ν_{im} and ν_{im}^k are 1 and K-vector standard normal variables assumed to be IID across consumers as well as across product characteristics and price. Similarly, D_{im} and D_{im}^k denote the demographic variables drawn from empirical demographic distribution data (consumption survey data). ε_{ijm} are IID (across consumers and across products) Type-I Extreme value taste shifters.

We denote the demand parameters as $\theta^d = (\beta', \alpha, \sigma', \lambda')$. Following literature, we separate the utility function into a mean utility part (δ_{jm}) and a consumer specific deviation ($\mu_{ijm} + \varepsilon_{ijm}$). We further define $\theta_2 = (\sigma', \lambda')'$.

The specification allows consumer's taste towards a characteristic $k \in \{1, 2, \ldots, K\}$ to shift about its mean β^k, with the heterogeneous terms $\sigma^k \nu_i^k + \lambda^k D^k$. For computational feasibility we restrict many of the σ's and λ's to be equal to zero in the empirical application. We do allow for heterogeneity of consumer preferences in price, age of the molecule, as well as the variety of products offered by the firm (number of SKUs). We define the utility from the outside option as

$$u_{i0m} = \varepsilon_{i0m}$$

[1]Close therapeutic category includes drugs for other parasitic diseases like Dengue, fever among others

[2]A product is a firm- molecule combination

The model predicted market share for product j in market m is given by

$$\begin{aligned} & s_{jm}(x, p, \delta, \nu, D; \theta_2) \\ & = \int \frac{exp[\delta_{jm} + \mu_{ijm}(x_{jm}, p_{jm}, \nu_{ijm}, D_{ijm}; \theta_2)]}{1 + \sum_{l \in J_m} exp[\delta_{lm} + \mu_{ilm}(x_{lm}, p_{lm}, \nu_{ilm}, D_{ilm}; \theta_2)]} dP_\nu(\nu_i) dF_D(D_i) \end{aligned} \tag{2.1.2}$$

where J_m denotes the total number of products produced in market m. Here P_ν and F_D denote the joint distribution of ν_{im} and D_{im} respectively.

2.1.2 Supply

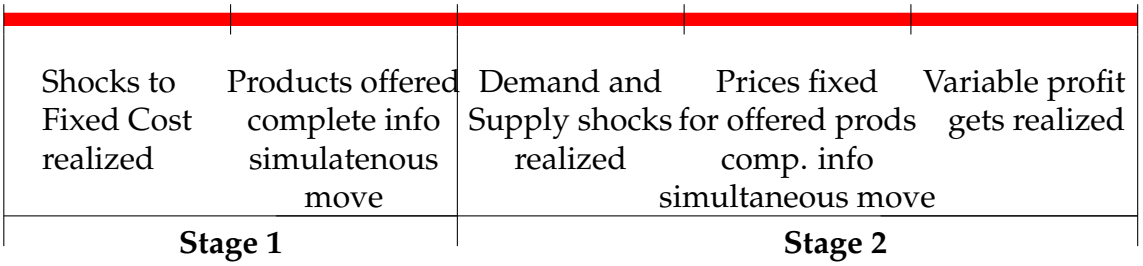
We model supply decisions of the firms as a two stage game. We assume that a firm is endowed with a predetermined set of products to choose from in each year. This set of products are essentially fixed for a firm across regions and across years in our analysis. However the number of potential firms in a region will vary across regions. The assumption of a predetermined set of products is justified by the fact that the molecules are developed following a complex R & D process which is assumed to be exogenous to the decisions of the firms. The time-line for the two-stage game, played by the drug manufacturers is given by:

1. In the first stage the firms observe the realization of shocks to the fixed costs. These shocks are not observed by the econometrician. These shocks are assumed to be firm-region-product specific. Firms have complete information about own shocks as well as shocks from competitors. They then simultaneously choose the products in each market taking into account expected profit for the set of products and incur fixed cost for each of the products.
2. Firms commit to the set of released products in stage 1 and then they observe the realization of demand and marginal cost shocks. These shocks

are unobserved by econometrician. Then, the firms simultaneously choose prices for all the released products.

In the stage 1, firms are assumed to know the distribution of shocks to demand and marginal cost, but they observe these shocks only after stage 2 is realized, after having committed the set of products to be released. In our specification, with inclusion of product dummies, these shocks include the region-specific valuations of the product. Since we control for product dummies and other detailed product characteristics, these errors should not capture any systematic effect that firms are likely to know prior to committing to their product choices. This type of timing assumptions are also used in Eizenberg [2014], and Wollmann [2014]. Next we describe the details of the game.

TIMING OF THE GAME



Pricing: Stage 2

The second stage decision of the firm involves setting the prices for the products that were released in stage 1. We assume the log of marginal costs for a drug j in market m depend linearly on observed cost shifters, w_{jm} and on an additive error term ω_{jm}:

$$\log(mc_{jm}) = w_{jm}\gamma + \omega_{jm} \tag{2.1.3}$$

where γ is the parameter vector to be estimated. We include molecule dummies for all 11 molecules, age of the molecule, dummy for big three firms, presence of firm in close therapeutic categories and number of years since the firm is active in a specific molecule as observable cost shifters (w_{jm}).

In the beginning of stage 2, each firm f observes the realization of demand and cost shocks (ξ_{jm}, ω_{jm}) for each product j chosen in stage 1. These shocks are not observed by the econometrician. Firms set prices for each product j, simultaneously in a complete information framework, with the goal to maximize profits. The profit maximization problem of a multi-product firm producing J_{fm} products (by firm f in market m) is given by

$$\max_{p_j, j \in J_{fm}} \left\{ \pi_{fm} = \sum_{j \in J_{fm}} (p_{jm} - mc_{jm}) s_{jm}(p_m) \times M - \text{Total Fixed cost} \right\} \tag{2.1.4}$$

where p_{jm} is the price charged by the firm f for product j in market m. M denotes the market size. s_{jm} denotes the equilibrium share of product j in market m. mc_{jm} is the constant marginal cost associated with product j in market m. Note that s_{jm} depends not only on p_{jm}, the actual price of good j in market m, but also the entire vector p_m, all prices of all goods in market m.

We assume that given any stage 1 history and any parameter values, stage 2 prices are determined uniquely in a pure strategy, interior Nash-Bertrand price equilibrium. We derive the first order necessary conditions from firms' profit maximization problem and write the equation system in the form of system of equations given by

$$p - mc = \underbrace{(T \times \Delta(p; \theta_2))^{-1} s(p)}_{\text{mark up}} \tag{2.1.5}$$

With J_m products in market m, the total number of products in all markets is denoted by $J = \sum_m J_m$. Here p and $s(p)$ are is a $J-$dimensional vectors of prices and market shares respectively. T is a $J \times J$ ownership matrix with $T_{ij} = 1$ if product i and j are produced by the same matrix and 0 otherwise, $\Delta_{i,j}$ is the derivative of the market share of product j with respect to the price of product i.

Product Offerings: Stage 1

In the first stage, firms observe the realization of fixed cost shocks and make product offering decisions with the understanding that their actions and their rival's actions will affect the variable profit in the second stage. This leads to strategic interaction among firms while making product offering decisions.

Each firm is assumed to have a pre-specified menu of products and each product has associated fixed cost which firm would incur conditional on offering the product in the market. In our specification, fixed costs are assumed to be firm-product-region specific. For each product j produced by firm f in market m, the fixed cost is assumed to take the following specification

$$F_{fjm} = W_{fjm}\theta + \nu_{fjm} \tag{2.1.6}$$

where θ is the vector of fixed cost parameters to be estimated. W_{fjm} are fixed cost covariates which include region specific covariates (region-group dummies), firm-product specific covariates (firm presence and number of SKUs offered by the firm for a molecule). ν_{fjm} is an error term with zero unconditional expectation, that is

$$E(\nu_{fjm}) = 0 \tag{2.1.7}$$

Note that this is a flexible fixed cost structure and allows for heterogeneity across firms, products and regions and stochastic variation about the mean across products.

Given our information structure, firms have complete information regarding product specific fixed costs for each potential product and knowledge about the distribution of demand and cost shocks (F_ξ, F_ω). So, while taking product offering decision, they form an expectation over the shock distributions to compute the hypothetical expected profits from any set of product offerings. The expected variable profit is given by

$$E_{\xi,\omega}\pi_{fm}(J_{fm}, J_{-fm}, x, w, p; \beta, \gamma, F_\xi, F_\omega) = \int_{\xi,\omega} \pi_{fm}(J_{fm}, J_{-fm}, x, w, p; \beta, \gamma, \xi, \omega) dF_\xi dF_\omega \tag{2.1.8}$$

Firms weigh the expected variable profit from different product combinations against the total fixed cost of releasing the set of products and offer that set of products that maximizes total expected profit of the firm. Once the product offering decision is made, firms incur fixed costs for these products.

Solution Concept and multiple equilibria

A Subgame Perfect Nash Equilibrium consists of product choices and prices which constitute a Nash equilibrium in every subgame. Similar to Eizenberg [2014] and Wollmann [2014], we assume existence of a pure-strategy SPNE for the two-stage game. In a complete information game, occurrence of multiple equilibria is a rule rather than an exception. In several empirical applications in entry literature, multiplicity of equilibria is handled by assigning a equilibrium selection mechanism and selecting an equilibrium and assuming that the data is generated under the assumed equilibrium. However, we do not assume

uniqueness or select any equilibrium. We rather use necessary conditions for equilibrium product selection to estimate entry parameters. These conditions lead to partial identification of entry parameters and we use tools from moment inequality literature to do the estimation and inference.

CHAPTER 3

IDENTIFICATION AND ESTIMATION OF PRODUCT ENTRY GAME: THE CASE STUDY OF INDIAN MALARIAL MARKET

3.1 Identification and Estimation

3.1.1 Demand

We assume that firms do not observe the realization of demand shocks until they have committed to the product choices. As already discussed, a key feature that differentiates firms operating in Indian pharmaceutical industry from pharmaceutical industry in developed countries is the high level of heterogeneity that persists among firms and products. The same generic molecule are produced by different firms, and are sold as different brands. Sometimes the products are differentiated in terms of quality and other unobservable characteristics.[1] It is hard to construct observable characteristics that would substantially explain the demand behavior observed in the data. Similarly, if we do not explicitly control for the quality of the product, it will appear in the unobservable part of the demand. Our product entry stage assumes that the firms are unaware of the demand unobservables while making product choice decisions. We believe producer unaware of the average product quality is too strong an assumption to make.

To take care of this problem, we exploit the panel structure of our data, and include product-specific dummy variables in the product characteristics. We

[1]For example, the branded generic firms claim to maintain a superior quality compared to unbranded generic drugs

have 185 products in total. Use of product specific fixed effects is strongly advocated in Nevo [2000b], Nevo [2000a], Nevo [2001]. Apart from product dummies, we also include weighted average price, age of the molecule (for the quarter), number of presentations (SKUs), revenue share of the firm in close therapeutic categories, and number of years since the firm is active in a given molecule, in the product characteristics. We also control for region dummies, and quarter dummies in our demand specification. Apart from Price, location of products in the characteristics space are assumed to be exogenous or at least determined prior to the revelation of consumer's valuation of product characteristics, and hence are assumed to be independent of the demand shocks.

Usually, the error term, as defined in demand specification, is the unobserved product characteristics. Once we allow for product dummies, the coefficients on these dummy variables capture the mean quality of the observed characteristics that do not vary across markets, and the overall mean of unobserved characteristics. Thus the error term is the unobserved region-quarter deviation from the overall mean valuation of the product. However, we assume firms observe and account for this deviation, which will influence the market-specific markup and will be correlated with prices. Thus, nonlinear least square estimates will be biased and inconsistent.

We use BLP instruments along with a set of other instruments to take care of endogeneity and also for identification of substitution patterns (See Berry and Haile [2014]). We use observed characteristics (excluding price), functions of product characteristics produced by same firm as well as produced by rival firms in the market to construct instruments. We will discuss the choice of instruments in detail in the next section.

Following Berry [1994], and BLP, estimation of demand parameters (θ) requires one to compute errors $\xi_j(\theta)$, interact these error terms with instruments to construct the GMM estimator. The main technical difficulties in the estimation are the computation of integrals defining market shares and the inversion of market share equations to obtain the error term. Given any parameter values, the mean utility of the products (δ_{jm}) is calculated by inverting a system of equations given by

$$s(\delta_{jm}, \theta_2) = S_{jm}, m = 1, \ldots, M$$

Unlike logit model and nested logit model, in BLP model, δ_{jm}'s can not be solved analytically. The BLP method incorporates a contraction mapping step in which one inverts the demand system to recover a vector of mean utility, that equates the predicted market shares with the observed market shares. BLP prove that the fixed point iteration used in the BLP scheme is guaranteed to converge. While this global convergence property is appealing, the BLP contraction mapping can be time consuming, especially when the sample size exceeds 5,000.

In order to speed up convergence, a common technique as suggested in Nevo [2000b] is to (a) relax the inner loop tolerance value in regions where the minimization of the GMM objective function is far from the true solution and (b) tighten the tolerance criterion as the minimization gets closer to the truth. However, this procedure may lead to incorrect estimates, as Dubé, Fox, and Su [2012] show that the inner loop tolerance must be set at 10^{-14} with the outer-loop tolerance at 10^{-6}.

To accelerate the convergence without being penalized for estimation bias, we adopt the squared polynomial extrapolation method (SQUAREM), a state-of-the-art algorithm that can operate directly on the fixed-point formulation

of the BLP contraction mapping. [2] Originally developed to accelerate the expectation-maximization (EM) algorithm, (see Varadhan and Roland [2008], Reynaerts, Varadhan, Nash, et al.) SQUAREM has been shown to be not only faster but also more robust (in terms of the success rate of convergence than the original contraction mapping procedure used in BLP. The advantage of SQUAREM is even more substantial when the sample size is large (as in our case) and when the initial values of the parameters are far from the truth.[3]. The details of the estimation routine is described in the appendix.

Choice of instruments

As is well-established, Identification of substitution parameters is crucially dependent on the choice of instruments. In our model, we also use instruments to take care of endogeneity of price which arises from two different sources. From our modeling assumptions, prices are set in stage 2 after the firms observe the realized errors, making the prices endogenous. Additionally, we combine the prices across SKUs to form an index at the molecule level using sales share as the weights. Since sales share is also likely to be correlated with the unobserved demand shock, it brings in an additional source of endogeneity. To take care of this, we construct instruments following Berry [1994] and BLP. Our identifying assumption is that the location of the product in the characteristic space is exogenous and is determined prior to the revelation of consumer's valuation of unobserved product characteristics. Given this assumption, we construct instruments (BLP instruments) using observed product characteristics excluding

[2] An alternative method to overcome the tolerance and speed issue would be to give up the contraction mapping altogether and use MPEC approach (impose share equations as constraints in the optimization problem) as advocated by Dubé, Fox, and Su [2012]

[3] see Chris Conlon's website for references and MATLAB codes on SQUAREM

price. The functions of these characteristics are correlated with markups and hence with prices. We use molecule age, age of the specific brand, and presence of firm in related therapeutic categories to construct instruments. The instruments are sums and sum of squares of values of same characteristics of other products offered by the firm (if the firm produces more than one products) and sums and sums of squares of the same characteristics of products offered by other firms.

We include rainfall in our set of instruments as malarial incidence is correlated with rainfall through prevalence of mosquitoes in the region. We also follow Romeo [2010] and include mean demographic characteristic (in our case mean of log per capita monthly expenditure) across regions in the set of instruments. Demographic moments are likely be correlated with both the marginal cost and markup or willingness-to-pay components of price and it is this correlation that potentially makes them valid instruments.

We also add a set of instruments that we prepare following Gandhi and Houde [2015]. Following insights from Berry and Haile [2014] they suggest to construct instruments referred to as "differentiation IVs". These instruments exploit the "local competition" structure of the products in the characteristic space. We use no of SKUs across different products and construct these instruments by using histogram of characteristic differences.

We use these instruments and estimate the demand parameters. These estimates are reported in table A.5. We then follow Reynaert and Verboven [2014], and construct optimal instruments in our final estimation. Given the set of initial estimates $(\hat{\beta}, \hat{\alpha}, \hat{\sigma}, \hat{\lambda})$, we construct the set of optimal instruments which includes (i) the exogenous variables (in our case all variables except price) (ii) An

estimate for price (constructed by projecting price on instruments), (iii) Jacobian matrix which is constructed as derivative of mean value with respect to the parameters (see Nevo [2000b] appendix for details).

Given that we use product dummies, it is suggestive to consider Hausman instruments to include in our set of instruments. These potential instruments are the prices of the same good in other regions. If we can claim exogeneity of demand shock of a region with respect to price in other region, then these instruments can be considered as valid instruments. However, in our case, firms charge the same price for a specific pack of a drug across all regions in India, hence, demand shock in one region in expected to correlated with prices across all regions.

3.1.2 Estimation of marginal cost parameters

Of the 11 drugs we consider, three drugs (chloroquine, S+P and Hydroxychloroquine) are under price control. For the price controlled molecules, we assume that each firm sets its price allowing for 12% lerner's ratio. This is similar to Dutta [2011] which also recovers marginal cost for drugs under price control by assuming 10% to 15% margin.

For drugs not under price control, we follow the set up as in (2.1.5) and estimate the marginal cost using the following relation

$$p - mc = \underbrace{(T \times \Delta(p;\theta_2))^{-1} s(p)}_{\text{mark up}}$$

where p is the observed vector of prices, $s(p)$ is the vector of observed market share, and $\Delta(p;\theta_2)$ is the matrix of derivatives which is constructed with the

estimated demand parameters. Here T is the ownership matrix where i, j-th element takes value 1 if both product i and j are produced by the same firm in the given market.

3.1.3 Estimation of fixed cost parameters

Given the demand and marginal cost parameters, we now estimate the parameters for fixed cost. For our fixed cost estimation, we define region-*year*[4] as a market. Hence, given our specification, F_{fjm} is the mean per year fixed cost for introduction of a product j by firm f in market m. We assume following parametric specification for F_{fjm}:

$$F_{fjm} = W_{fjm}\theta + \nu_{fjm}$$

where W_{fjm} are the covariates for fixed cost and θ is 5-dimensional parameter vector for fixed costs to be estimated. ν_{fjm} is market-firm-product specific unobservable with $E(\nu_{fjm}) = 0$.

In this set up however, a unique equilibrium is not guaranteed. This brings well known complications in fixed cost estimation since, we as econometricians, can not uniquely map the observed data to a specific equilibrium predicted by the model without making further assumptions. Even if we specify a distribution for fixed costs, we can not specify the probabilities of product-choice outcomes and hence we can not write down a likelihood function (Tamer [2003]). In various empirical applications, the estimation strategies mostly rely on different equilibrium selection mechanisms. For example, the framework proposed

[4]In doing variable profit analysis we define region-quarter as a market

in Bresnahan and Reiss [1991] and used in Dutta [2011], [5] predicts unique equilibrium for the number of products offered, by assuming that the products are homogeneous. However, this would not allow us to incorporate product variety in our analysis of endogenous product choices. On the other hand, Berry [1992] and Mazzeo [2002], rank the firms in terms of profitability, and in equilibrium allow the most profitable firm to move first. They assume symmetry among firms in the post-entry profit game leading to symmetric competition effect. This results in equal number firms entering the market across all equilibria. They use this condition to construct their estimation strategy. In our model, the demand side explicitly models the product differentiation and hence, post-entry profit function leads to asymmetric competition effects. Hence, in our model, firms do not preserve ranking in terms of profitability, and profitability depends on set of rivals competing with the firm. This implies, in our model, number of firms and products across equilibria may vary depending on parameters.[6] These results arise since our model allows for heterogeneity of fixed cost as well as post-entry profit across firms.

Therefore, we follow the strand of literature that does not impose unique equilibrium assumption and instead obtain partial identification via necessary equilibrium conditions (Pakes, Porter, Ho, and Ishii [2011], Ho and Pakes [2013]). Readers can refer to Ho and Rosen [2015] for a recent survey on various applications using this methodology.

Our data does not cover all months in 2007 and in 2013, hence we use product offering information from 2008 to 2012 in estimating fixed cost parame-

[5] Dutta [2011] divides firms into three groups, but firms are completely homogeneous in these three groups and identity of the firms is assumed away

[6] For example, if in a market, there are three firms, one is relatively bigger and other two are relatively smaller firms. Given parameter values, we can imagine two equilibria, in one equilibrium, only the big firm enters and in other equilibrium, only the other two firms enter.

ters. The estimation strategy relies on the assumption that the observed product choices and prices support an SPNE of the two-stage game. Then, a necessary equilibrium condition is that no firm can increase its expected profit by unilaterally altering its first-stage product choices, taking into account the effect of those deviations on second stage prices. Such necessary conditions will imply bounds on fixed costs. We will use one-step deviations (dropping a single product from the offered list or adding a single product not offered by the firm, but was present in the menu of potential products) to construct our bounds[7]. In particular, for each offered product, an upper bound on fixed cost can be derived by computing the counterfactual profit on dropping the product. Given that the firm has chosen to offer the product in the market, it must be that the expected additional gain from releasing the product exceeds the fixed cost of releasing the product. Hence, this difference in expected variable profits must be an upper bound for fixed costs. Similarly, for a product that was in the menu of potential products, but the firm chose not to offer in the market, it must be that the fixed cost of releasing the product exceeded the expected rise in profit by adding the product. Hence, the expected change in variable profits from addition of unreleased potential products would serve as a lower bound for the fixed cost.

It is worth pointing out that an alternative approach would be to generalize familiar discrete choice theory to allow for multiple interacting agents, explicitly solve the set of equilibria and use partial identification techniques to do the estimation and inference. The ideas behind this approach has been developed in Tamer [2003], Ciliberto and Tamer [2009], Andrews, Berry, and Jia [2004]. These two approaches are not nested. Pakes [2010] provides an excellent discussion

[7]Note that the identified parameter space by these necessary moment conditions *may* be non-empty even when equilibrium does not exist

of the two approaches and also draws a comparison of assumptions as well as properties of estimates in both the approaches.

Bounds on fixed cost parameters

We construct fixed cost parameters by calculating the counterfactual profits by adding a product and dropping a product from current set of offered products. We denote J_{fm} by the set of products produced by firm f in market m. We denote by $\mathscr{J}^{p}_{fm}$, the potential set of products the firm f has in its potential menu for market m.

Consider a product j offered by firm f in market m, i.e. $j \in J_{fm}$. Denote the variable profit by the firm from offering the product portfolio J_{fm} by $\pi(J_{fm}, J_{-fm})$, where J_{-fm} denotes the set of products produced by all other firms (all firms except f) in market m. Counterfactual profit of the firm from not including this product in J_{fm} is given by $\pi(J_{fm} \setminus j, J_{-fm})$. Given our assumptions, it must be that

$$F_{fjm} \leq E_{\xi,\omega}\left[\pi(J_{fm}, J_{-fm}) - \pi(J_{fm} \setminus j, J_{-fm})\right]$$

where $E_{\xi,\omega}$ denotes the firm's expectation over the true distribution of demand and supply shocks associated with all products. Note that given our assumptions, the firm does not observe the realizations ξ, ω, but has knowledge of the distributions (F_ξ, F_ω), and hence the firm weighs the added expected profit against the fixed cost of introducing the product in market m. Similarly, for a product $j \in \left\{\mathscr{J}^{p}_{fm} \setminus J_{fm}\right\}$, not offered by firm f in market m, but in the menu of potential products, it must be that

$$F_{fjm} \geq E_{\xi,\omega}\left[\pi(J_{fm} \cup j, J_{-fm}) - \pi(J_{fm}, J_{-fm})\right]$$

In words, the condition for upper bound states that, a deviation by firm f which eliminates one of its offered products must not be profitable, that is, firm f's saving in fixed costs can not exceed the expected drop in its variable profit. Analogously, if j was not offered, a lower bound for fixed cost is available: a deviation that adds j to firm f's portfolio must not be profitable, implying the added fixed costs must exceed the expected gain in variable profits. Computational details on the construction of the bounds are included in the appendix.

Bounds, endogeneity problem and solution

Given our fixed cost specification, we have $F_{fjm} = W_{fjm}\theta + \nu_{fjm}$. Applying conditional expectation to the bounds above, we will have

$$W_{fjm}\theta + E(\nu_{fjm}|\text{Product Offered}) \leq E\left\{E_{\xi,\omega}\left[\pi(J_{fm}, J_{-fm}) - \pi(J_{fm} \setminus j, J_{-fm})\right]\right\}$$
$$W_{fjm}\theta + E(\nu_{fjm}|\text{Product not Offered}) \geq E\{E_{\xi,\omega}\left[\pi(J_{fm} \cup j, J_{-fm}) - \pi(J_{fm}, J_{-fm})\right]\}$$

The expectation in the right hand side of the two inequalities above is identified. However, if we can assert that $E(\nu_{fjm}|\text{Product Offered}) = 0$ and $E(\nu_{fjm}|\text{Product not Offered}) = 0$, then we can use the inequalities to identify upper and lower bounds on fixed cost parameters. Note that, from (2.1.7), we have assumed that unconditional expectation of the error term is 0, i.e. $E(\nu_{fjm}) = 0$. However, in our information framework, we assume that the firms have the knowledge of the unobservables ν_{fjm} while making the decision on product choices. Hence, the mean of ν_{fjm} conditional on firm choices need not be zero, that is, the terms $E(\nu_{fjm}|\text{Product Offered})$ and $E(\nu_{fjm}|\text{Product not Offered})$ need not be zero.

We observe the upper bound only for the products that are offered. For these

products,

$$E\left\{E_{\xi,\omega}\left[\pi(J_{fm}, J_{-fm}) - \pi(J_{fm} \setminus j, J_{-fm})\right]\right\} - W_{fjm}\theta - E(\nu_{fjm}|\text{Product Offered}) \geq 0 \tag{3.1.1}$$

The firm must have chosen those products to offer that has favorable unobservable fixed cost shock, where a favorable shock is a smaller value (more negative value) of the unobservable. This implies:

$$E(\nu_{fjm}|\text{Product Offered}) \leq 0$$

Note that since $E(\nu_{fjm}|\text{Product Offered}) \leq 0$, from (3.1.1), we can not ensure that

$$E\left\{E_{\xi,\omega}\left[\pi(J_{fm}, J_{-fm}) - \pi(J_{fm} \setminus j, J_{-fm})\right]\right\} - W_{fjm}\theta \geq 0$$

Following similar arguments, we can show that $E(\nu_{fjm}|\text{Product not Offered}) \geq 0$. Given this condition, we can not ensure

$$W_{fjm}\theta \geq E\{E_{\xi,\omega}\left[\pi(J_{fm} \cup j, J_{-fm}) - \pi(J_{fm}, J_{-fm})\right]\}$$

This is the "selection problem" raised in Pakes, Porter, Ho, and Ishii [2015] and Pakes [2010]. PPHI as well as Eizenberg [2014] have proposed ways to handle this selection problem. Eizenberg [2014] assumes bounded support for fixed costs. Note that, we do not observe upper bound for the products that are in the potential product list, but not in the list of offered products. Similarly, we do not observe lower bound for the products that appear in the offered product list and are not offered in the market. He replaces these missing bounds with conservative estimates for each firm. Specifically, for each firm, he calculates the drop in variable profit from excluding the blockbuster product for a firm and this provides a conservative estimate for the missing upper bounds. In our framework, the potential set of products of a firm is fixed across all regions. In some regions, we observe cases where a product is never released in our sample.

Similarly, a firm's profitability from a product varies across regions, hence it is hard to define a blockbuster product for a firm across all regions.

We address the problem using monotone instruments. These types of instruments are discussed in PPHI (see their conditions in assumption 3) and Manski and Pepper [2000].

Suppose we have instruments $h_u(z)$ and $h_l(z)$, which satisfy following conditions:

$$\begin{aligned} &(i) h_u(z) > 0 \text{ and } h_l(z) > 0 \qquad (ii) E(h_u(z) \cdot \nu_{fjm} | \text{Products Offered}) \geq 0 \\ &(iii) E(h_l(z) \cdot \nu_{fjm} | \text{Products not Offered}) \leq 0 \end{aligned} \tag{3.1.2}$$

The first condition implies that the instruments take positive value. So when we multiply the instruments with the inequality, the direction of inequality remains preserved. The second and third conditions describe the restriction of the relationship between the structural error terms and the instruments. The second condition implies that the instruments for upper bounds ($h_u(z)$) must be positively correlated with ν_{fjm}. The third condition implies that the instruments for lower bound ($h_l(z)$) must be negatively correlated with ν_{fjm}.

To further clarify the conditions on upper bound, note that the unconditional expectation of the error term ν_{fjm} is zero. Hence, as the sample size N increases, by law of large numbers, $\frac{1}{N}\sum \nu_{fjm} \to 0$. However, for the products offered in the market, for which we can construct upper bounds, the average, $\frac{1}{N}\sum(\nu_{fjm}|\text{product offered})$ does not converge to 0 and converges to a negative number. Our condition implies that the weighted average of the selected error terms converges to a positive number where we use our instruments are weights. This requires, our weights should be higher when the selected error terms are higher (when ν_{fjm} for the offered product is positive number or small

negative numbers), and our weights should be smaller when the selected error terms are smaller (when ν_{fjm} for the offered product is a large negative number). The explanation is similar for the instruments for lower bounds.

Using these instruments, we can address the selection problem. By pre-multiplying the instruments with inequalities and taking expectation, we have

$$\begin{aligned} &h_u(z)W_{fjm}\theta - E\left\{h_u(z)\cdot E_{\xi,\omega}\left[\pi(J_{fm},J_{-fm}) - \pi(J_{fm}\setminus j, J_{-fm})\right]\right\} \\ &\qquad\qquad \leq -E(h_u(z)\cdot \nu_{fjm}|\text{Product Offered}) \leq 0 \\ &E\{h_l(z)\cdot E_{\xi,\omega}\left[\pi(J_{fm}\cup j, J_{-fm}) - \pi(J_{fm},J_{-fm})\right]\} - h(z)W_{fjm}\theta \\ &\qquad\qquad \leq E(h_l(z)\cdot \nu_{fjm}|\text{Product not Offered}) \leq 0 \end{aligned} \tag{3.1.3}$$

If we can plausibly construct $h_u(z)$ and $h_l(z)$ satisfying the above conditions then, we can take care of the selection problem.

To ensure the weighted average for the error terms from upper bound is nonnegative and weighted average from error terms from lower bound to be non-positive, we first restrict the support of the error terms. We assume that

Assumption 1. $\sup F_{fjm} < \infty$, *and* $\inf F_{fjm} > \infty$.

Now let us discuss the construction of instruments. For example, for upper bounds we need some variables which are positively correlated with ν_{fjm}, so that for the error terms that are selected while calculating, the weighted average will be positive. Note that for a product that is offered in the market, the realized unobserved shocks would take smaller and more negative values. For a product not offered in the market, the realized unobserved shocks would take larger and more positive values. To construct such instruments, we need variables that systematically take larger positive values for the products that are offered in the market, and smaller positive values for the products that are not offered

in the market, so that the expectation of the unobservable interacted with the instruments will take desired signs as mentioned in (3.1.2).

We can however use demand shifters to address this selection problems. We use firm presence (revenue share of a firm in close therapeutic categories) and number of SKUs for a given molecule by a firm to construct these instruments.

In our framework, we observe firm presence in close therapeutic categories (other parasitic diseases like Dengue, fever other than malaria) in a given region.[8] Our demand analysis reveals that if a firm is popular in close therapeutic categories, it is likely to gain more market share in the malarial drug as well. This implies, a firm with higher firm presence in a region is more likely to offer higher number of products compared to a region where it has lower firm presence. Hence, a firm with higher firm presence in a region is likely to get more favorable fixed cost shocks. Note that in our notation a favorable shock would mean smaller and more negative values. This means, if we consider (1 – firm presence), then it satisfies the conditions to be a potential candidate to be an instrument. First, (1 – firm presence) takes non-negative values for each possible value of firm presence, as firm presence is a share function and lies between 0 and 1. Also, for a firm, (1 – firm presence) is positively correlated with the unobservable shock. This is because, for a firm with higher (1 – firm presence) in a region, the firm has lower firm presence, the shocks would be unfavorable, and hence shocks would take larger and more positive values. For a firm with lower (1 – firm presence) in a region, the firms will have higher firm presence, realized shocks would be favorable, and the shocks would take smaller and more negative values.

[8]To be precise, we construct revenue share of a firm in close therapeutic categories in each region for each year

Next we discuss plausibility of 'number of SKUs' as a candidate for potential instrument. Here we exploit the regional variation in our data to construct our instruments. When firms take decision to release products across different regions in India, they take into account the demand characteristics of the regions. Through conversation with various industry people, we learned that firms categorize different regions into different groups in terms of profitability and demand characteristics. For example, while making product offering decisions, firms categorize all big cities and all low-income regions into two different groups. The point we want to make is that, for a set of regions in a group, a given firm's observed decisions in one region can carry information about unobserved entry shocks that the firm realizes in other regions. Specifically, for two regions, region A and B with similar characteristics, if we observe a firm offering multiple product varieties (SKUs) of a given molecule in region A, it likely to find it profitable to offer the same molecule in region B. Using this intuition, we construct instruments that is going to be positively correlated with the unobservable shocks. Each firm produces a number of varieties of each molecule, but the firm may choose to sell only a subset of all potential varieties in a region. Typically, in low-income regions firms choose to sell only packs containing tablets, whereas in high-income regions the firm offers liquids and injections also. Hence, if we consider deviation from potential number of SKUs, that is (Potential number of SKUs – Actual number of SKUs) as a potential candidate for instruments. First, this deviation will take nonnegative values only. Secondly, this deviation moves in the same direction as the shocks. For example, in an unfavorable market where this deviation is higher the shocks take higher values. In a favorable market the deviation is lower, and also the shocks take lower values.

Hence, if we consider a positive increasing function of (1 − firm presence) and deviation from maximum form number as $h_u(z)$, multiply this with (ν_{fjm}|Products Offered) and take expectation, then it is going to give a smaller weight to more negative values and a bigger weight to less negative and positive values, and we assume that the expectation is going to be nonnegative.

For construction of $h_l(z)$, we use firm presence of a firm in a region and number of SKUs offered by the firm in similar regions as potential candidates. Following analogous arguments, we can show that firm presence is negatively correlated with entry shocks, that is, if firm presence for a firm is small in a region, the firm faces unfavorable shocks in the region, and this implies the realization of the shock takes larger positive values in a region. Similarly, in a region with high firm presence, the firm faces favorable shocks, and this implies the shocks are smaller. Similarly, if region A and region B are similar, and a firm finds it profitable to release more varieties of a molecule in region A, it is likely to face lower fixed cost for releasing the molecule in region B. That means, the unobservable shocks for the firm will be negatively correlated with the shocks. Hence if we consider a positive increasing function of firm presence and form number, multiply this with (ν_{fjm}|Products not Offered) and take expectation, then it is going to give a bigger weight to more negative values and a smaller weight to less negative and positive values, and we assume that the expectation is going to be negative.

In practice, we consider

$$h_u(z) = (1 - \text{firm presence}) + \log(1 + \text{max SKUs - actual SKUs})$$

$$h_l(z) = (\text{firm presence}) + \log(1 + \text{actual SKUs})$$

The moment conditions are now given by

$$\begin{aligned}
&\frac{1}{N_u}\sum_{jm}\left\{h_u(z)W_{fjm}\theta - h_u(z)\cdot E_{\xi,\omega}\left[\pi(J_{fm},J_{-fm}) - \pi(J_{fm}\setminus j, J_{-fm})\right]\right\} \leq 0 \\
&\frac{1}{N_l}\sum_{jm}\left\{h_l(z)\cdot E_{\xi,\omega}\left[\pi(J_{fm}\cup j, J_{-fm}) - \pi(J_{fm},J_{-fm})\right] - h_l(z)W_{fjm}\theta\right\} \leq 0
\end{aligned} \tag{3.1.4}$$

where the moment conditions are derived from taking averages of profit inequalities, N_u denotes the number of inequalities for construction of moment conditions for upper bound and N_l denotes the number of inequalities for construction of lower bound. W_{fjm} denotes the covariates for fixed cost. We divide regions into three groups: regions with low income, regions with high income and relatively higher incidence of malaria and regions with high income and relatively lower incidence of malaria. We also include firm presence in a region and number of potential SKUs for a firm in the set of covariates.

We construct the profit inequalities for each firm across all the regions. Note that we will have an inequality for upper bound for a firm and product that the firm offers in the region. Similarly, an inequality for lower bound is constructed for a product that is in the menu of potential products, but the firm does not produce in the region. We divide firms into two groups: the big three firms and all other firms. For each region, we construct moment conditions for upper bound by averaging the inequalities for upper bound for each firm group. Similarly, we construct moment condition for lower bound by averaging the inequalities for lower bound for each firm group in a region.

3.1.4 Inference

We construct sets in which the sunk cost parameters will uniformly lie 95% of the time. Inference based on inequalities is less straightforward than infer-

ence based on equalities (for example generalized method of moments) since inequalities provide only one-sided restrictions. Note that our moment conditions are written in the form

$$E(m(W_{fjm}, \theta)) \leq 0$$

$$\text{The identified set is } \Theta_I = \{\theta : E(m(W_{fjm}, \theta)) \leq 0\}$$

where W_{fjm} are the covariates used in our entry estimation, and $m = (m_1, \ldots, m_J)$ are the J moment conditions we use to estimate the bounds for θ. We use methodologies developed in Kaido, Molinari, and Stoye [2015][KMS] to construct confidence intervals for fixed cost parameters.

We report element wise confidence interval for our parameter vector θ. To do this, we consider the projection of Θ_I in a specific direction. For example, for first element of θ, we are interested in the projection of Θ_I in the direction p and $-p$, where p is the unit vector with first element equal to 1. As confidence interval for this object, we report the projection of a relaxation of the sample inequality conditions, that is for the k-th element of θ, we solve:

$$\begin{aligned} &\max / \min \theta_k \\ &\theta \in \Theta_I \\ &\text{s. t. } \frac{\sqrt{n}\bar{m}_j(x, \theta)}{\hat{\sigma}_j(\theta)} \leq \hat{c}_n(\theta) \end{aligned}$$

where $\hat{\sigma}_j(\theta)$ is an estimator of asymptotic standard deviation of the moment conditions. Here $\hat{c}_n(\theta)$ is the critical value and the 95% coverage is achieved by properly calibrating $\hat{c}_n(\theta)$. The critical value is computed by checking feasibility of a linear program across bootstrap repetitions. While calibrating the critical value, we select the binding moments following the generalized moment selection as discussed in Andrews and Soares [2010].

3.2 Estimation Results

The parameters to be estimated are variable profit parameters $(\beta, \alpha, \sigma, \lambda)$ and We now report the results from estimation of our model from section 2.1.

3.2.1 Demand parameters

It is instructive to begin with a simple, descriptive outlook on the demand system. Table A.4 reports the demand estimation results based on the simple logit model, which is obtained from the demand model described in section 2.1.1 by setting all the σ and λ coefficients to zero. Estimation is performed via linear regression after following the transformation by Berry [1994]. The first column reports OLS estimates of the mean utility parameters (β), while second column employs 2SLS to account for endogeneity of price using the instruments in section 3.1.1. These results demonstrate the importance of correcting for price endogeneity. While demand is downward sloping in both specifications, the price sensitivity coefficient is larger (in absolute value) in the IV case. Given that price is the only endogenous variable, the first stage F is informative. F-stat value of 83.75 satisfies the thumb rule of validity of instruments.

Full-model (BLP) estimation results: The random-coefficient demand model allows for more realistic substitution patterns than the simple logit, and captures consumer heterogeneity along important dimensions. We allow random coefficients for price, molecule age, and number of SKUs for each product. We allow for random shocks drawn from normal distribution and also interact the variables with demographic data. Table A.5 provide estimation results for

demand parameters. These results are reported from the model without using the optimal instruments. The estimated parameters include mean utility parameters (β), coefficient of interactions of normal random error terms with covariates (σ) and coefficients of interactions of demographic variables with covariates (λ). We also include product dummies, region dummies, quarter dummies as well as interaction of dummy for firm1 with region dummies in the mean utility specification.

The mean price coefficient although negative is not precisely estimated at 5% level of significance. Coefficient of interaction of price with log of expenditure and age are significant. The coefficient of interaction of price with normal error draws is both economically and statistically insignificant, suggesting that most of the heterogeneity is explained by demographics. An individual with more monthly expenditure and higher age tend to be less price sensitive. This is important, as different regions in India have very different income levels. A region with high income level will tend to have more consumers with less price sensitivity. To illustrate this point, we plot the distribution of price coefficient from two regions with high income level (Mumbai and Gujurat) and two regions with relatively low income level (Bihar and Odisha) in Figure A.6.[9]

We now discuss the significance of the demand estimates and highlight the variation in demand patterns across different regions in India. Note that a firm's incentive to release a product in a region is guided by the expected variable profit in the region. Given that firms charge same price across all regions, regional demand patterns are going to play crucial role in influencing the incentives of the firms while making product release decisions.

[9] Average per capita income of Bihar is 28,774 Indian rupees, Odisha is 49,241 Indian rupees, Gujurat is 96,976 Indian Rupees.

First we calculate, in each quarter across all regions, the percentage rise in the total market share of all goods except for chloroquine and S+P (i.e. all "inside goods" combined except chloroquine and S+P) in response to a 1% drop in the price of all products. This gives us a broad idea of how aggregate market shares across different regions would respond as each price drops by 1% due to price control. The average elasticities across different regions are demonstrated in the Figure A.7. It varies from in the range of 1.67 to 8.57 across different regions.

To gain more intuition on regional variation, we present willingness to pay (WTP) for increasing mean utility by one unit across different regions in India in table A.6. This is calculated by taking the average of inverse of price coefficient across individuals in each region and converting it in terms of Indian rupees. It is worth pointing out that it varies significantly across regions. Average consumers in low-income-regions are willing to pay much less compared to an average consumer in high-income-region.

We also report our results from estimation with optimal instruments in table A.7. These results are qualitatively similar to our earlier estimates with initial instruments. Except for the coefficients of interaction of molecule age with age, and interaction of No of SKUs with age, all other statistically significant coefficients preserve their signs and comparable in magnitude. However, as expected, the variances of the substitution parameters are reduced after we use optimal instruments. We use our earlier estimates (from initial instruments) for our calculations in following sections.

3.2.2 Marginal cost parameters

Given the estimated demand parameters, we estimate the Molecules under price control are generally allowed a margin of 10% to 15% (see Dutta [2011] page 167). For the molecules under price control, we impose a lerner's ratio of 12% and we recover marginal cost using the following transformation.

$$mc = p(1 - 0.12) \tag{3.2.1}$$

For molecules not under price control, we recover the marginal cost using the first order conditions given by

$$p - mc = \underbrace{(T \times \Delta(p; \theta_2))^{-1} s(p)}_{\text{mark up}}$$

where p is the observed vector of prices, $s(p)$ is the vector of observed market share, and $\Delta(p; \theta_2)$ is the matrix of derivatives which is constructed with the estimated demand parameters. Here T is the ownership matrix where i, j-th element takes value 1 if both product i and j are produced by the same firm in the given market.

After recovering the marginal cost for each product, we regress the marginal costs on a set of regressors. The regressors include age of the molecule, number of presentations produced by the firm for the molecule, number of years since the firm is active in the molecule, presence of the firm in related therapeutic categories. We also include dummy for big three firms and dummies for each molecule in our regression analysis.

Table A.8 reports the marginal cost parameter estimates. All the parameter estimates are significant at 95% level of significance and R-square is close to 0.9. Marginal cost of producing older molecules is less compared to new

molecules. Cost of producing molecules with higher number of presentations is higher compared to lower number of presentations. If a firm is already popular in related therapeutic categories, it faces less cost of production. The estimates also suggest that if a firm is already active in related therapeutic categories the marginal cost of production is higher. At first glance, it looks surprising, however when a firm first starts selling a product, it generally sells tablets and gradually sells other presentations of the molecule over time. Since marginal cost of production of injections and liquid forms is higher, the coefficient is positive. Also, the big three firms face lower marginal cost of production.

Table A.9 reports the average Lerner's ratio across different molecules. The average is taken across all firms producing the same molecule. For the molecules with price control, the Lerner's ratio is 12% which comes from our imposition of 12% rule. For other molecules the average Lerner's ratio numbers are reasonable. Conversation with managers from different firms reveals that the numbers are in expected range.

3.2.3 Fixed cost parameters

Table A.10 reports the confidence intervals for fixed cost parameters. The bounds are the 95% confidence intervals which uniformly cover the projection of the identified set. Fixed cost parameters are positive and significantly different from zero, revealing that the fixed costs faced by the firms are positive.

We divide regions in India into three categories on the basis of average per capita income and prevalence of malaria. Regions in category 1 include relatively poor regions. Estimates reveal that the dummy for fixed cost in the poor

regions is strictly higher compared to the dummy for less poor regions. It implies, at any given level of price control, the profitability of low-income-regions is less compared to high-income-regions. This has important welfare implications since as price control is imposed, more firms would exit from low-income-regions compared to high-income-regions.

To make sense of the fixed cost estimates, as well as to illustrate the variation of fixed costs across regions and across firms, we report the average fixed costs as a fraction of variable profit for big three firms in Table A.11. Each of the big three firms produce multiple products across different regions. We calculate total profit earned by these firms across different regions every year to get total firm-region level annual profit. We divide this with the number of molecules produced by the firm to get the annual per molecule profit across different regions. We take the average across years to get the average annual per molecule region level profit for each of these firms.

We have set-estimates for each of the fixed cost parameters. We consider the mid-points of each of these sets and calculate the fixed cost at the parameter vector consisting of the mid points. The numbers reported in the table A.11 shows fixed costs across regions as a fraction (in percentage) of the average annual variable profit across different regions.

Table A.11 shows that fixed costs vary across firm and across regions. In some regions, fixed costs are a significant fraction of variable profit. Fixed costs for IPCA Laboratories, the leader in the malarial drug market in India, as a fraction of variable profit is on an average lower compared to other two firms. In profitable regions like Mumbai, all the three firms have very low fixed costs compared to variable profit. IPCA laboratories also faces very low fixed costs in

majority of the regions including North East, Rajasthan, Jharkhand. It is worth pointing out that consistent with our estimates, IPCA Lab has close to 80% market share in North East region of India.

There is significant heterogeneity across firms and across regions in terms of fixed cost of entry. In some regions like West Bengal Rest all the three firms face very high fixed cost. In our data, these firms have negligible market presence in these regions. Both Shreya life science and Zydus Cadila face very different fixed costs across different regions. Hence, once price control is imposed, incentives the firms to offer products across different regions will vary significantly. If a firm faces lower fixed cost in a region, the firm will continue producing the product even after price control. In regions with higher fixed costs, the firm will find it profitable to withdraw its products. Similarly, since fixed costs are heterogeneous across firms, there will be differential product withdrawal by firms in response to a price control policy.

3.3 Using the estimated model: Counterfactual Analysis

We analyze the effect of price control for the malarial molecules (currently not under price control). Section 3.3.1 discusses the background of price control, Section 3.3.2 provides practical details and results from our counterfactual exercise.

3.3.1 Background of counterfactual exercise

What happens when Government imposes price control? Understanding price control policy has significant welfare implications as Government of India has been using price control policy extensively. The policy covers all drugs that are listed in National List of Essential Medicines. The number of drugs under government price controls increased to 652 in 2013, including combination products, from just 74 bulk drugs in 1995, with an estimated size of the total market being affected close to USD13.13 billion, or 30% of the whole market.[10]

In our analysis, out of 11 molecules, 3 malarial molecules were under price control since 1995. Price control policy in 2013 added three more molecules under price control. However, it is reported that the government has been scrutinizing and considering price control for all drugs used to treat different therapeutic categories including malaria.[11]

Motivated by this background, in our first counterfactual exercise, we impose price control on all the 11 malarial drugs in our sample, allow for different levels of price control, and simulate the product offering decisions of different potential firms across different regions. We also compute related consumer welfare. Consumer welfare depends not only on prices but also on availability of products, and hence product withdrawal can affect consumer welfare negatively. It is worth pointing out that, a provision in the drug price control act, 2013 explicitly states the concern of product withdrawal of the firms, and the policy discourages firms to discontinue the sale of the product. We reproduce the part of the government order here to strengthen the point we want to make:

[10] (Reference - Link)

[11] The therapeutic categories are anti-diabetic drugs, cardiovascular drugs. cancer, viral infections, asthma, tuberculosis and malaria– source: Business Standard (Link)

"Any manufacturer of scheduled formulation, intending to discontinue any scheduled formulation from the market shall issue a public notice and also intimate the Government in Form-IV of schedule-II of this order in this regard at least six month prior to the intended date of discontinuation and the Government may, in public interest, direct the manufacturer of the scheduled formulation to continue with required level of production or import for a period not exceeding one year, from the intended date of such discontinuation within a period of sixty days of receipt of such intimation."
-[para 21- DPCO 2013]

3.3.2 Counterfactual Exercise: Details and Results

Motivated by the setting above, we ask the following question: "Given a level of price control, where price of *all* the products are controlled, how many of the products will a firm release in a given market". In practice, in our counterfactual, we will fix the lerner's ratio ($\frac{p-mc}{p}$) at different values and evaluate product offering decisions of the firms in each scenario.

Each potential firm in a given region can produce a menu of products. According to our modeling assumption, each firm will make the product offering decision in the following way: Given a menu of k products the firm can choose to produce no product, all the k products or a subset of products. This gives 2^k possibilities for the given firm. The firm evaluates expected variable profit from each of these combinations with the total fixed cost from offering these products and chooses that combination which maximizes the total expected profit. Note that, in the price control exercise, price of the goods are given. However, the expected variable profit of a firm will still depend on presence of other firms in

the market. since equilibrium market share a firm will be lower if it faces more competitors and vice versa. This implies, the firm while taking its decision, will take into account the strategic considerations in terms of entry of other firms as well. Given that on an average close to 20 potential firms operate in a region and each firm can produce multiple products, it ends up in a very high dimensional problem. To compute firm's product offer decision, we need to compute the expected variable profit of each firm at *all* possible combination of product portfolios across all firms. Since, our model assumes complete information, we may also end up with multiplicity of equilibria.

To get around this problem, we make several simplifying assumptions. We first restrict our attention to four products only - Artesunate, Arthemether + Lumefantrine, Arteether + Artemotil, and Artesunate + Sulfadoxine + Pyrimethamine. We focus on these four products only, since these molecules are new and more effective molecules and hence we are interested in the release decisions of these products. We further assume that each firm ignores the strategic considerations while making the product offering decisions, that is each firm will consider its monopoly profit from different product combinations and decide the set of products it would offer in a market.

Note that the results we will get from this exercise will be conservative. By restricting our attention to four products only, we rule out the cannibalization effects of other products of the same firm, that is if we allow for other products of the same firm to be released in the market, the expected variable profit from the above products will be even lower without affecting the fixed cost, leading to even less probability of product release. Similarly, if we allow firms to behave strategically, the expected variable profits would be even lower and firms would

be even more discouraged from offering more products. Hence, if we see firms withdrawing products in our exercise, allowing for other products and strategic interactions will strengthen our results.

In the counterfactual exercise, we calculate expected variable profit for each product combination of each firm. Given a price control rule, we fix the price of each product. We use product characteristics of the products in 2012 for variable profit calculations. For the products that are not produced in 2012, but are in the list of potential products, we use average product characteristics across other time periods in the given region. We draw 100 vectors from empirical ξ and ω distributions and use demand and marginal cost parameters to compute the variable profit at each of the error vectors. We then take the average to compute the expected variable profit. We compute the variable profit allowing at Lerner's ratio equal to 0.08 and 0.15.

To compute total profit, we also compute the fixed costs of offering the set of products in the market. Our fixed cost estimates are average per molecule per year fixed cost. We add fixed costs across molecules to get total fixed costs. Given that we estimated bounds for each parameter, we use the mid point of each bound for estimating fixed costs.

The results from counterfactual are reported in table A.12. Lowering the profit from 15% to 8% leads to firms withdrawing products across different regions. For example, in Odisha, one of the regions with highest malarial cases, at 15% margin 9 firms sell Artesunate, 4 firms sell A+ L, 9 firms sell A + A and 2 firms sell A+S+P. As margin is reduced to 8%, the number of firms reduce to 4, 3, 4, and 1 respectively. In relatively high-income regions like Gujurat, Mumbai, Marathwada, Tamilnadu, and Rajasthan both under 15% and 8% margin,

relatively higher number of firms operate. However, consequences of price control is more significant in relatively low-income regions. In regions like Bihar, Chhatishgarh, Jharkhand, North East, and Odisha, number of firms after price control is much lower. Although number of malaria cases are higher in these markets, these are not very profitable. Hence, even under 15% margin, not many firms operate in these areas. However, once margin is further reduced, the firms tend to exit the markets.

We compare consumer welfare at 15% and 8% to see whether reducing margin from 15% to 8% leads to an increase in consumer welfare. Following Small and Rosen [1981] consumer surplus of consumer i with utility function v_{ij} takes the following form:

$$CS_i = \frac{1}{\alpha_i}\left[\gamma + \ln\left[1 + \sum_{j=1}^{J} \exp(v_{ij})\right]\right]$$

where γ is Euler's constant and v_{ij} is the deterministic component of utility for person i from product j. We integrate out over unobserved taste heterogeneity to obtain consumer surplus given by:

$$CS = \int CS_i dF_D dP_\nu$$

where F_D and P_ν stand for demographic distribution and distribution of normal random errors respectively. From our calculations, the consumer welfare at 15% margin exceeds the consumer welfare at 8% level. This indicates to an optimal price control policy that would maximize consumer welfare. The intuition is straightforward: since fixed cost estimates are positive, at marginal cost pricing, with zero margin, no product will be released in the market. Hence, consumer welfare is lowest at marginal cost pricing. As higher margins are allowed, more products enter the market. Hence, firms would release more products in the market resulting in an increase in consumer welfare. A very high increase in

margin would only lower welfare since menu of products to be released by firms is fixed. Hence, at some point, consumer welfare will attain an optimal level. The results from this exercise to determine optimal price control allowing for strategic interaction among firms is current work in progress and results will be updated soon.

To get a "rough" idea regarding the plausibility of the above results, we collected evidence on the products that were brought under price control in 1995. It is striking to note that out of 74 molecules under DPCO 1995, 27 are no longer under production. We also referred to a report published in June 2015 by IMS[12] which reports that after the price control in 2013, a shift towards production of non-controlled products is being observed. Smaller and mid-sized firms are increasingly opting to make non-controlled drugs due to better margins offered. It is also worth pointing out that there are evidences suggesting that price control policy was not successful in achieving desired goals in China, South Korea or Philippines, where price control led to lowering rather than increasing of access to drugs.

3.4 Concluding Remarks

The article studies the consequences of imposition of price control on access to drugs and consumer welfare. We estimate a model that treats both product choices and prices as endogenous decisions by the firms. We relax assumptions which guarantee unique equilibrium outcome, and propose a novel way to address selection bias issues. A detailed model of differentiated product cost

[12] "Assessing the Impact of Price Control Measures on Access to Medicines in India" - IMS Report 2015

and demand along with regional variation, allows us to perform a fine-grained analysis of the impact of price control policy on access to drugs by taking into account the incentives of the firms across different regions.

An important limitation of this work is the static framework, which prohibits us from considering the role played by forward-looking behavior of the firms. A firm in our model exits if the current expected variable profit is dominated by fixed costs. The prediction will be different if we allow the firm to consider its forward looking behavior while taking the decisions. For example, experience in one product market or in one region, can potentially improve firm performance in a related product market in future. Thus, entry into a market is determined not just by the profits in that market but also by its future impact on profitability in other markets (Gallant, Hong, and Khwaja [2010]). We address this issue to some extent by controlling for firm presence in related therapeutic categories which captures experiences of the firm in a region. We view this static model as a useful step towards better understanding the issue of equilibrium product variety in the market and leave a full model allowing for dynamic considerations for future research.

In our framework, we only discuss the role of price control in ensuring access to drugs and maximizing consumer welfare. In 2005, India along with many developing countries under the regime of TRIPs agreement of WTO, has ratified complete patent protection. However, under TRIPs, the governments of these countries have reserved the rights to control prices and impose compulsory licensing. Interaction of compulsory licensing and price control policy may lead to very different dynamics for firm incentives which is beyond the scope of our analysis. We however would like to recognize that even after a decade of patent

protection, compulsory licensing is exercised only in very few cases. On the other hand, we see extensive use of price control; for example, Indian government has included 652 drugs under price control in 2013, starting from 74 drugs in 1995. Hence, understanding effects of price control is of first order importance for policy design. Interaction of compulsory licensing and price control and its effect on consumer welfare is an important question that we leave for future work.

APPENDIX A

FIGURES AND TABLES

A.1 Figures

Figure A.1: Number of Firms across different Molecules

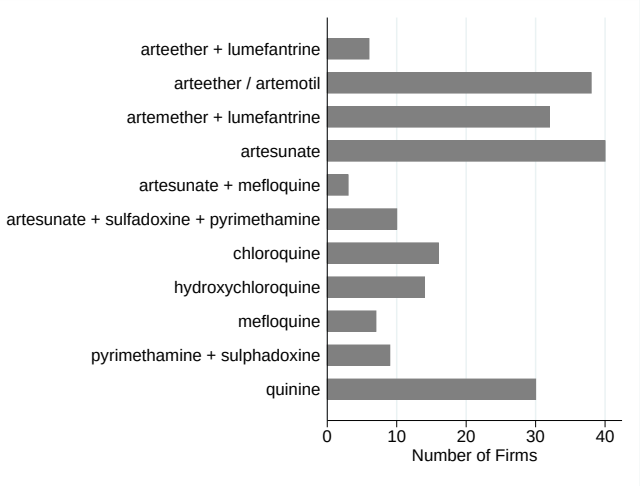


Figure A.2: Quarterly Total sales of Malarial Drugs

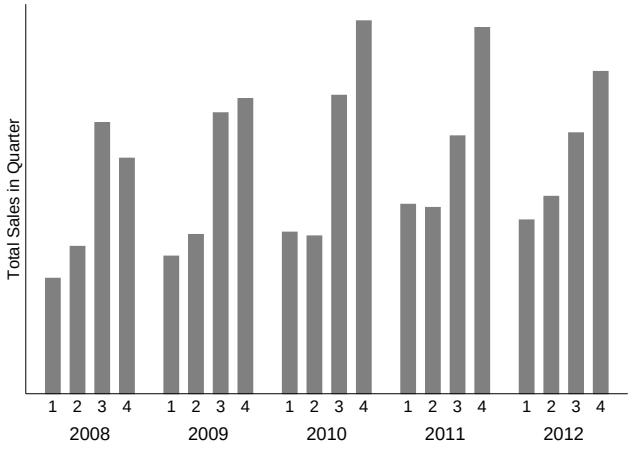


Figure A.3: Average Number of Malaria Patients per Year across Different Regions

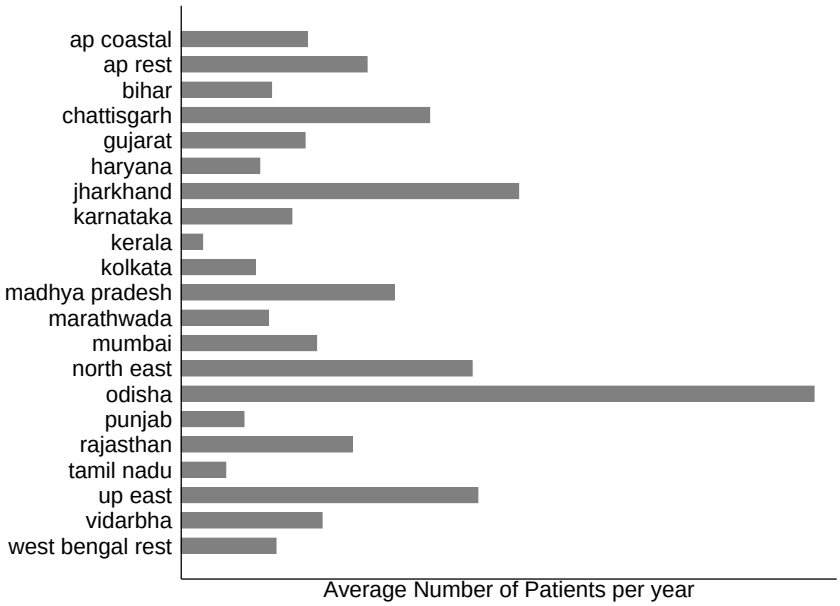


Figure A.4: Average Number of Firms Across Different Regions

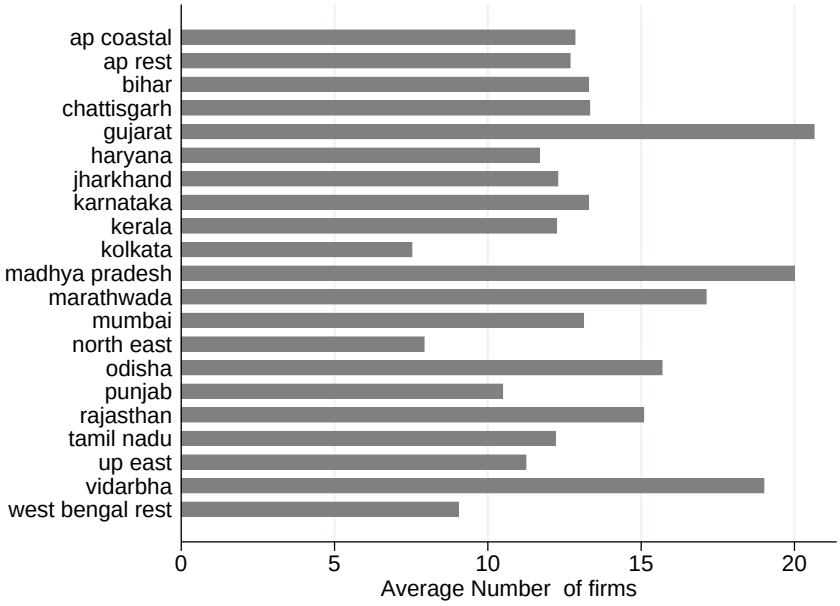


Figure A.5: Malaria across Different Countries (Source: WHO)

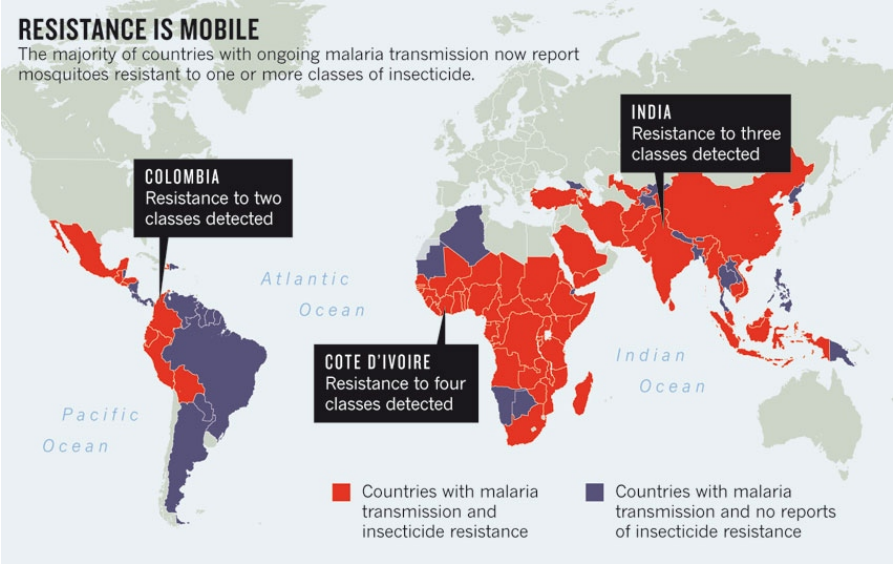


Figure A.6: Frequency Distribution of price coefficient

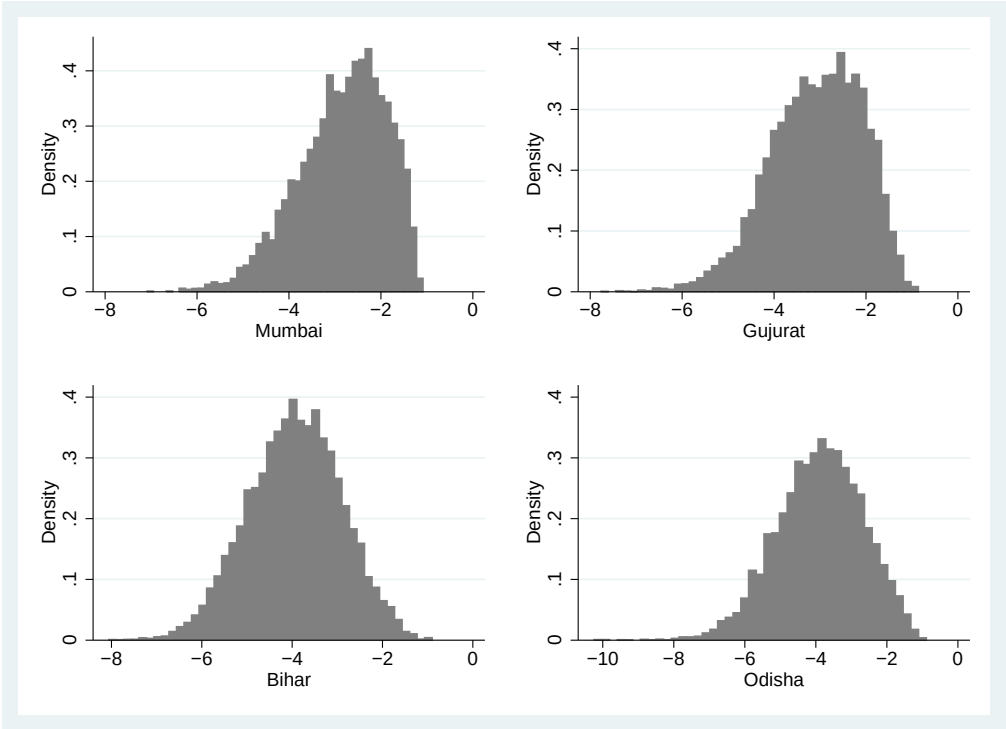
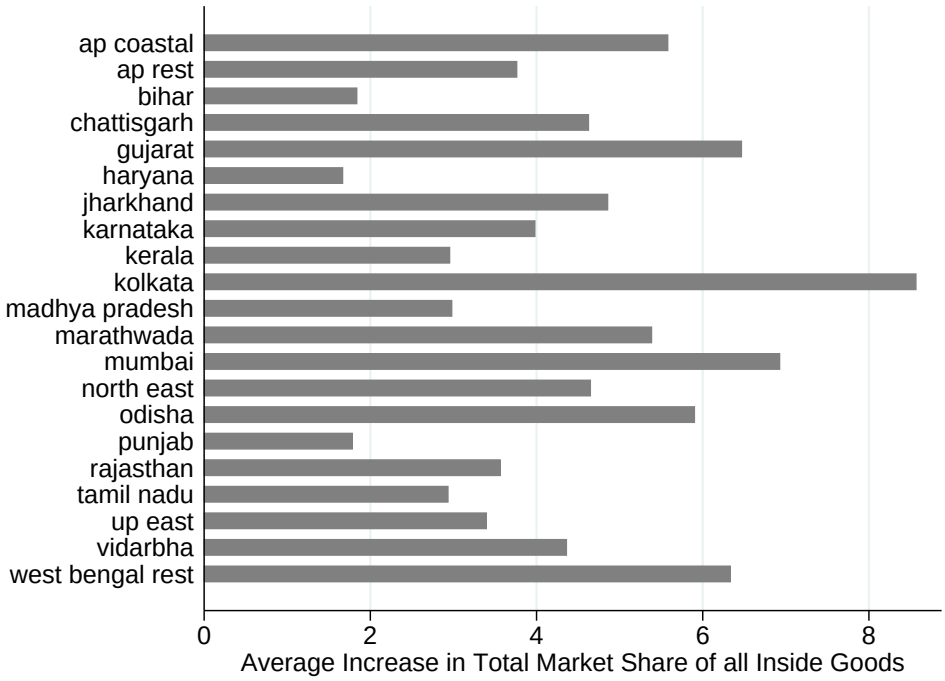


Figure A.7: Response of all "inside goods" combined (Except Chloroquine and S+P) to 1% price drop



A.2 Tables

Table A.1: Average Price of Molecules per Patient (in Indian Rupees)

Molecule	Average Price per patient (Indian Rupees)	No of Patients (in Million)
Price Control from 1995		
Pyrimethamine + Sulphadoxine	6	193
Chloroquine	8	1110
Hydroxychloroquine	59	104
Price Control from 2013		
Quinine	183	28
Artesunate + Sulfadoxine + Pyrimethamine	206	5.8
Mefloquine	267	1.7
Not under price control		
Arteether/Artemotil	117	123
Artemether + Lumefantrine	180	41.1
Artesunate	202	54.3
Arteether + Lumefantrine	263	1
Artesunate + Mefloquine	447	0.4

* Molecules with drug resistance are highlighted in red

*Price is per-patient-price for a complete treatment

*1 USD ≈ 64 Indian Rupees

Table A.2: Average Price per Patient (in Indian Rupees)

Average Price per patient (Indian Rupees)				
Molecule	mean	std	min	max
Price Control from 1995				
Pyrimethamine + Sulphadoxine	6	4	2	36
Chloroquine	8	2	3	16
Hydroxychloroquine	59	11	10	81
Price Control from 2013				
Quinine	183	38	91	351
Artesunate + Sulfadoxine + Pyrimethamine	206	34	123	360
Mefloquine	267	51	186	358
Not under price control				
Arteether/Artemotil	117	45	38	390
Artemether + Lumefantrine	180	55	81	415
Artesunate	202	47	75	398
Arteether + Lumefantrine	263	78	126	411
Artesunate + Mefloquine	447	127	293	615

* Molecules with drug resistance are highlighted in red

*Price is per-patient-price for a complete treatment

*1 USD ≈ 64 Indian Rupees

Table A.3: Herfindhal Index across Regions-over Year

Region	Average Herfindhal Index	Herf 2008	Herf 2009	Herf 2010	Herf 2011	Herf 2012	Herf 2013
Gujarat	20.79	16.07	18.6	19.04	18.65	23.41	28.94
West bengal rest	21.66	37.29	24.68	18.77	16.2	15.08	17.94
Mumbai	28.1	28.11	27.03	23.97	27.21	27.02	35.26
Marathwada	28.53	19.97	21.29	33.19	33.31	28.94	34.5
Madhya pradesh	29.04	24.19	22.82	31.24	30.31	31.43	34.25
Kerala	30.05	37.33	29.9	24.23	20.65	31.18	36.99
Bihar	34.45	34.08	34.81	29.82	29.6	31.12	47.31
Chattisgarh	39.51	30.38	28.11	32.94	35.55	50.38	59.7
Odisha	42.36	39.76	42.07	42.25	39.71	40.21	50.16
Ap coastal	43.77	28.8	34.55	38.75	45.31	49.33	65.87
Up east	43.78	42.85	47.66	46.96	44.64	36.55	44.05
Karnataka	44.41	33.49	40.84	48	41.57	43.79	58.8
Rajasthan	46.21	41.44	43.68	43.11	44.07	47.85	57.1
Ap rest	46.31	36.53	41.85	43.12	50.17	47.12	59.07
Vidarbha	46.37	46.16	37.91	50.47	43.41	47.79	52.51
North east	46.45	22.03	28.57	38.59	32.73	66.88	89.92
Jharkhand	46.87	36.3	45.21	53.31	64.7	43.69	38.03
Tamil nadu	47.87	43.85	44.92	46.43	58.39	50.25	43.39
Kolkata	53.77	59.09	59.79	58.83	44	49.55	51.36
Haryana	58.76	53.87	57.02	56.35	63.69	58.78	62.87
Punjab	69.61	59.85	65.89	71.2	78.56	72.88	69.3

Table A.4: Descriptive Results, Logit Demand

VARIABLES	OLS	IV
Price	-0.686***	-1.967***
	(0.0300)	(0.0983)
molage	-1.399***	-0.775*
	(0.378)	(0.396)
form_no	5.865***	5.177***
	(0.122)	(0.136)
firmpres	1.261***	1.311***
	(0.0771)	(0.0802)
brandage	2.430***	1.989***
	(0.402)	(0.419)
Constant	-9.428***	-6.885***
	(0.915)	(0.958)
Observations	19,735	19,735
R-squared	0.734	0.709
Product FE	Yes	Yes
Region FE	Yes	Yes
Quarter FE	Yes	Yes
First Stage F	-	83.75

Standard errors in parentheses

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

Table A.5: Results from BLP Model

VARIABLES	Coefficients	SE	t-stat
Price	-5.6461	4.7521	-1.1881
Age of the molecule	-5.3648	9.1711	-0.5850
No of SKUs	18.7488	19.1457	0.9793
Firm presence (in close therapies)	1.4167	0.0979	14.4729
No of years since firm active	1.8582	0.6511	2.8538
Price(sigma)	0.0001	1.1781	0.0000
Price*[log(Expen)]	2.2523	0.4166	5.4057
Price*[log(Expen)]^2	-0.5365	0.8068	-0.6649
Price*age	0.4903	0.0411	11.9262
Price*Rural-Urban dummy	0.2729	0.6739	0.4050
molecule age(sigma)	0.0001	6.1233	0.0000
molecule age*[log(Expen)]	2.2217	2.1659	1.0257
molecule age*age	0.9157	0.1037	8.8320
No of SKUs(sigma)	0.0001	15.7610	0.0000
No of SKUs*[log(Expen)]	-7.0760	4.4908	-1.5757
No of SKUs*age	-2.3966	0.2250	-10.6496

Includes Product Dummies, Region Dummies, Quarter Dummies

Number of Observations: 19,732

Table A.6: Average Willingness to Pay for 1-year newer molecule

Region	Avg. Willingness to Pay (Indian Rupees)
Bihar	27.43
Jharkhand	28.07
Up east	28.67
Odisha	28.76
Madhya Pradesh	29.49
Chattisgarh	29.78
North East	33.47
Rajasthan	34.21
West bengal rest	34.46
Karnataka	34.66
Gujarat	36.29
Marathwada	36.65
Vidarbha	36.92
AP Rest	37.08
AP Coastal	37.35
Kolkata	37.96
Tamil nadu	38.92
Mumbai	39.43
Haryana	39.64
Punjab	41.26
Kerala	43.58

Table A.7: Results from BLP Model with Optimal Instrument (from Reynaert and Verboven [2014])

VARIABLES	Coefficients	SE	t-stat
Price	-7.2590	19.2289	-0.3775
Age of the molecule	0.4205	4.5980	0.0915
No of SKUs	-6.3894	6.5199	-0.9800
Firm presence (in close therapies)	1.3498	0.1007	13.4102
No of years since firm active	2.9868	0.5264	5.6735
Price(sigma)	0.0001	0.8699	0.0000
Price*[log(Expen)]	2.9565	0.2161	13.6821
Price*[log(Expen)]^2	-1.9861	2.5863	-0.7679
Price*age	1.4427	0.0237	60.8375
Price*Rural-Urban dummy	-0.5334	0.5674	-0.9401
molecule age(sigma)	0.0001	2.0356	0.0000
molecule age*[log(Expen)]	-1.0905	0.8769	-1.2436
molecule age*age	-0.3107	0.0270	-11.4995
No of SKUs(sigma)	0.0001	3.9463	0.0000
No of SKUs*[log(Expen)]	1.9491	0.5965	3.2676
No of SKUs*age	3.0092	0.0849	35.4458

Includes Product Dummies, Region Dummies, Quarter Dummies

Number of Observations: 19,732

Table A.8: Results from Marginal Cost Estimation

VARIABLES	(1) Estimates
Molecule age	-0.1604**
Number of SKUs	0.4575**
Firm presence in related therapies	-0.0205**
Number of years since firm active	0.4399**
Dummy for Big three	-0.0550**
R-Squared	0.8987
11 Molecule Dummies Included	
Number of Observations: 19,732	

Table A.9: Average Mark-up across Molecules

Molecule	Average Marginal Cost	Lerner's Ratio
Price Control since 1995		
Pyrimethamine + Sulphadoxine	0.055	12
Chloroquine	0.07	12
Hydroxychloroquine	0.518	12
Price Control From 2013		
Quinine	1.393	24.779
Artesunate + Sulfadoxine + Pyrimethamine	1.54	25.59
Mefloquine	2.048	23.698
Not Under Price Control		
Artesunate	1.47	27.414
Artemether + Lumefantrine	1.348	26.476
Artesunate + Mefloquine	3.887	15.394
Arteether + Lumefantrine	2.028	22.957
Arteether / Artemotil	0.725	41.592

Number of Observation: 19,732

Lerner's Ratio: $\frac{p-mc}{p}$

Molecules with drug resistance are highlighted in red

Table A.10: Fixed Cost Bounds

Fixed Cost Estimates	
VARIABLES	95% CI [KMS(2015)]
Dummy-Region category 1	[0.1235 , 0.1258]
Dummy-Region category 2	[0.0408 , 0.0420]
Dummy-Region category 3	[0.0231 , 0.0242]
Presence of firm in close therapeutic categories	[0.2008 , 0.2118]
No of SKUs	[0.0201 , 0.0224]]

* Confidence Interval at 95%

*Generalized moment selection allowed [AS 2010]

Table A.11: Fixed Cost as a fraction of variable profit for big three firms across regions (in percentage)

Region	IPCA Laboratories	Shreya life sciences pvt ltd	Zydus Cadila
AP Coastal	14.13	25.9	35.54
AP Rest	23.41	17.73	29.84
Bihar	38.34	55.75	62.82
Chattisgarh	21.16	82.63	121.13
Gujarat	14.37	90.27	6.05
Haryana	12.08	81.7	36.15
Jharkhand	12.27	24.78	42.1
Karnataka	7.25	16.17	20.31
Kerala	9.21	30.05	94.04
Kolkata	29.29	362.42	79.18
Madhya Pradesh	6.45	79.19	35.87
Marathwada	12.86	23.02	7.97
Mumbai	6.98	4.03	6.11
North East	6.17	178.85	23.41
Odisha	14	39.23	44.39
Punjab	13.38	43.7	47.13
Rajasthan	2.01	12.41	8.9
Tamil nadu	8.71	47.41	26.54
Up east	10.75	18.32	14.02
Vidarbha	8.7	27.78	21.67
West bengal rest	161.79	122.48	469.08

Table A.12: Counterfactual Results: Number of firms across different regions under price control

	Artesunate		A + L		A + A		A + S + P	
Region	15%	8%	15%	8%	15%	8%	15%	8%
Ap coastal	10	5	5	5	7	2	1	1
Ap rest	5	3	5	1	5	3	1	1
Bihar	6	5	9	8	6	4	0	0
Chattisgarh	1	1	3	3	3	3	0	0
Gujarat	22	19	15	11	16	11	3	2
Haryana	4	3	6	4	4	1	1	1
Jharkhand	2	1	2	1	4	3	1	1
Karnataka	9	4	6	4	9	4	2	1
Kerala	7	2	4	3	8	5	0	0
Madhya pradesh	14	7	13	7	18	9	1	0
Marathwada	17	14	12	10	11	9	1	0
Mumbai	15	13	15	12	13	8	2	2
North east	3	2	1	1	4	1	1	1
Odisha	9	4	4	3	9	4	2	1
Punjab	5	3	7	4	8	4	0	0
Rajasthan	17	15	15	13	15	15	4	3
Tamil nadu	11	7	6	3	9	5	1	1
Up east	10	7	9	8	8	8	0	0
Vidarbha	15	10	12	5	11	8	2	0
West bengal rest	2	0	1	1	1	1	0	0

A + L: Artemether + Lumefantrine

A + A: Arteether + Artemotil

A + S + P: Artesunate + Sulfadoxine + Pyrimethamine

Entries are number of firms at 15% and 8%

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