Price Controls with Imperfect Competition and Choice Frictions: Evidence from Indian Pharmaceuticals*

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(Job Market Paper)

December 11, 2024

Abstract

Price control policies are often deployed in many important markets, such as healthcare. In the presence of common market failures—imperfect competition or choice frictions—the impact of such policies on market outcomes and welfare is ambiguous. We provide novel analysis of these forces in the context of a large-scale pharmaceutical price control policy in India. We find the policy lowered the prices of branded drugs by 24% and increased their sales by 36%, with minimal impact on entry, exit, and diffusion of new molecules. The standard revealed preference framework implies that the policy increased consumer surplus by 23% because it corrected monopoly distortions without disrupting supply. However, we present novel evidence that choice frictions lead consumers to overvalue expensive brands relative to cheaper alternatives of similar quality. Once we account for these frictions, we find that the consumer surplus gains are 30% smaller and that total welfare declines, as the policy unintentionally steers consumers toward costly overvalued brands. Finally, we assess how to effectively set price ceilings and evaluate alternative nonprice regulations.

*We are grateful to our advisors Matthew Gentzkow, Heidi Williams, Liran Einav, Arun Chandrasekhar, and Jose Ignacio Cuesta for their invaluable guidance and advice. We thank Claudia Allende, B. Douglas Bernheim, Matthew Brown, Dante Domenella, Lily Liu, Erzo Luttmer, Neale Mahoney, Grant Miller, Manoj Mohan, Melanie Morten, Maria Polyakova, Adam Rosenberg, Helena Roy, Natalia Serna, Christopher Snyder, Neeraj Sood, Shoshana Vasserman, Alessandra Voena, Ali Yurukoglu, and seminar participants at Stanford University, Dartmouth College, and ASHE 2024 for valuable comments and suggestions. Marzieyh Aghaei, Sean Chen, and Saberi Mallick provided excellent research assistance. We acknowledge financial support from the Stanford King Center, Stanford Institute for Economic Policy Research, Hewlett-Packard Stanford Graduate Fellowship, and Leonard W. Ely and Shirley R. Ely Graduate Student Fellowship.

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1 Introduction

High and rising drug prices are a central policy issue, especially in low- and middle-income countries where consumers pay pharmaceutical costs almost entirely out of pocket. In India, approximately one-quarter of the population—325 million people—reports foregoing treatments because of costs (Government of India, 2019), and 220 million people report taking on debt to pay for essential medications (Government of India, 2020).

In response to these affordability challenges, policymakers often implement price controls that cap the prices firms can charge consumers (Cockburn et al., 2016). The impact of price controls on market outcomes and welfare is ambiguous when either firms have market power or consumers face choice frictions (e.g., have mistaken beliefs). A well-established literature predicts that, if pharmaceutical markets are competitive, price controls disrupt supply and lead to drug shortages, ultimately negating the benefits of lower prices (e.g., Arrow, 1951; Glaeser and Luttmer, 2003). However, if pharmaceutical firms exercise market power to mark up their prices, price controls reduce prices without disrupting supply, improving access to important drugs. If consumers optimally choose what they value, as is typically assumed in standard welfare analysis, increased (or decreased) access to drugs improves (or reduces) welfare. In healthcare, however, another frequent market failure arises when consumers have mistaken beliefs about a drug's benefits (Arrow, 1963). In such cases, welfare predictions that hinge on revealed preference can be inaccurate or even misleading—a previously unexplored issue in price control discussions. For instance, a consumer purchasing a drug after a price cut could be harmed if she overvalues the drug and is better off without it.

In this paper, we provide a novel empirical analysis on the role of market power and choice frictions in shaping the welfare impacts of a large-scale pharmaceutical price control policy in India. Using comprehensive market data and a natural experiment, we estimate the causal effect of the Indian policy on prices, sales, and product availability. In addition, we collect novel survey data to evaluate choice frictions and recover measures of the true utility of pharmaceutical products. In doing so, we address a longstanding limitation of studies in this setting: a lack of reliable data on quality. Finally, we develop and estimate a model of demand and supply to characterize preexisting market failures, estimate key primitives, evaluate the Indian policy, and assess alternative price and nonprice regulations.

The Drug Price Control Order of 2013 (DPCO) set price ceilings for 870 drugs considered essential for public health in India. Together, these drugs constitute 20% of the Indian pharmaceutical market by sales, directly impacting more than a billion people. The price ceiling is the unweighted average price of all the brands of a drug. (A brand is a distinct name used by different firms to sell the *same* drug.) Mechanically, the price ceiling is binding

only for expensive brands. Consumers prefer some of these expensive brands over cheaper brands of the same drug. For example, the drug Ramipril-5mg is sold by the multinational Sanofi as Cardace and by the Indian firm FDC as Ziram. In 2012, Cardace cost four times more than Ziram but captured three times the market share.

To evaluate the market impacts, we first estimate the effects of the Indian policy on demand and supply by comparing regulated and unregulated products before and after the policy. We find a 24% price decrease for brands above the price ceiling and a 5% price decrease for brands below the price ceilings, suggesting that the policy reduced price both statutorily and via increased competition. These price reductions led to a 36% increase in sales for expensive brands above the price ceilings. In addition, there was an overall increase of 6% in the consumption of regulated drugs, evidencing market expansion. On average, we do not find either meaningful changes in product exit or entry or any effect on the launch of new drugs in India within six years after the policy.[1] Thus, the typical concern that price controls reduce the supply of regulated products does not appear to be of major relevance.

Do these findings mean that the Indian price controls policy improved welfare? The answer is yes if brand preferences reflect consumers' choosing products that provide them with the most utility. Compared to many high-income countries, India has weaker regulation of pharmaceutical manufacturing that may not filter out substandard brands. Quality could therefore vary across brands of the same drug. Brand preferences reflect consumers optimally choosing more expensive brands that offer higher quality. However, consumers may favor expensive brands over cheaper substitutes of the same quality because of limited information (Bronnenberg et al., 2015) or reliance on informal and underinformed physicians (Das et al., 2022), who may also be influenced by pharmaceutical marketing (Narendran and Narendranathan, 2013). The presence of such information and agency issues, which we refer to as choice frictions, would mean that choices no longer reflect true utility. If so, the standard welfare analysis could be inaccurate and misleading (Bernheim and Rangel, 2005). To accurately assess the welfare effects of the policy, we need alternative and reliable measures of true utility.

We use a sophisticated shopper approach, in the spirit of Bronnenberg et al. (2015), to measure the true utility of different brands. We conducted a novel survey of 617 licensed physicians, recording the brands they use for their *own* treatment. In healthcare, physicians are likely the group of consumers with the best possible information. We specifically selected only licensed physicians who are well informed as measured by a number of metrics. Furthermore, the physicians' choices are not distorted by agency issues because we ask them about their choices for themselves. For these reasons, we interpret these physicians' choices

[1] We also find no meaningful impact of the policy on the global development and diffusion of new drugs.

as reflecting their true utility.

We find that physicians are more likely to buy some of the cheaper brands manufactured by specific Indian companies. For example, physicians are considerably less likely to choose the expensive multinational brand Cardace and are more likely to buy the cheaper Indian brand Ziram. Physicians prefer *specific* domestic brands, rarely selecting many other domestic brands. We consistently find these patterns across multiple drugs and therapeutic markets, suggesting that some cheaper domestic brands offer similar quality to expensive multinational alternatives.

We formulate a model of demand and supply to quantify welfare and assess alternative policies, accounting for supply responses and consumer choice frictions. We estimate the model in five important therapeutic markets: angiotensin-converting enzyme (ACE) inhibitors, antacids, calcium channel blockers, statins, and diabetes. We leverage policy-induced price variation to estimate consumer preferences and firms' costs. To capture choice frictions, we measure the gap between consumer and physician choices, controlling for other factors such as price sensitivity that influence the trade-off between quality and price.

We first quantify the welfare effects of the Indian policy under revealed preference, following previous empirical studies on price controls (Glaeser and Luttmer, 2003; Davis and Kilian, 2011; Cuesta and Sepúlveda, 2021). Our estimates reveal significant market power, with firms charging prices 2–10 times their estimated marginal costs. The Indian policy effectively reduced prices without inducing many exits, reducing costs for inframarginal consumers and improving affordability for marginal consumers. Under revealed preference, consumer surplus increases. In most markets, the policy improved total social welfare by correcting market power. An exception is the diabetes market, where the policy led to the exit of one highly valued product and reduced social welfare, highlighting a common downside of price controls.

Once we account for choice frictions, the gain in consumer surplus is 30% smaller. The policy mechanically lowered prices for expensive brands, steering consumers toward them and away from cheaper brands of comparable quality. While these marginal consumers anticipated a utility gain (hence their decision to switch), the actual gain is smaller or even negative because these brands were overvalued. The true gain in consumer surplus ranges from \$0.65 to \$4.24 per year per consumer in the therapeutic market. In 2013, the average consumer paid \$54.90 for statins, which constituted 9% of the median household's consumption budget;[2] the Indian policy improved consumer surplus by \$4.24 per consumer—gains that equal 7.9% of statin costs or 1% of the median consumption budget.

[2]In comparison, the average American spends 8% of her consumption budget on *all* healthcare expenses (Bureau of Labor Statistics, 2023).

Although consumers gain, total social welfare decreases by \$0.02–\$2.64 per consumer per year once we factor in loss of firm profits. These results highlight that the interaction between market power and choice frictions is crucial for evaluating price controls. Absent choice frictions, price ceilings can correct monopoly distortions and improve welfare. However, when consumers overvalue certain products, high markups efficiently steer consumers away from these products—similarly to a corrective "tax." By lowering this corrective tax, the Indian policy unintentionally reduces welfare, even without causing major supply-side disruptions.

Next, we evaluate the optimal price ceilings. If price ceilings are too low, high-utility products exit, resulting in lower consumer surplus and social welfare. For price ceilings close to the median brand price, price ceilings strike a balance between reducing markups and preventing exit. However, because consumers overvalue expensive brands, any drug-level price ceiling disproportionately impacts expensive overvalued brands and increases their consumption. Although these policies benefit consumers, there are efficiency losses even under the best drug-level price ceiling. To improve efficiency, regulators can set granular price ceilings at the product level based on primitives. For example, regulators can set cost-based caps using coarse information on the upper bound of costs, robustly improving consumer surplus and welfare.

Instead of regulating prices, regulators may attempt to reduce choice frictions. In an ideal scenario where all choice frictions are eliminated, consumer surplus would increase by \$0.59 to \$11.09. Previously undervalued firms benefit at the expense of overvalued firms. This intervention achieves 80% of the first-best surplus gain in the ACE inhibitors market, where choice frictions are the major market failure. However, in other markets, significant product differentiation remains even absent choice frictions, leaving firms with substantial market power. As a result, targeting choice frictions alone usually provides limited benefits, ranging from 0% to 40% of the first-best surplus gains. Combining both price and nonprice regulations to address both market failures effectively is crucial.[3]

Our paper primarily contributes to three strands of literature. First, we advance the literature on the economics of price controls. A large body of research has shown, from both theory and practice, that price controls are harmful in competitive markets because they reduce the supply of high-quality products (Olsen, 1972; Raymon, 1983; Deacon and Sonstelie, 1991; Glaeser and Luttmer, 2003; Davis and Kilian, 2011; Diamond et al., 2019). Research on price controls in the presence of market failures is more sparse, comprising a small set of theoretical studies (Salop and Stiglitz, 1977; Yohe, 1978; Smith and Williams, 1981) and an even smaller set of empirical papers on two market failures: market power

[3]We also suggestively evaluate other commonly used nonprice regulation: government entry, generic substitution, and quality standards.

(Cuesta and Sepúlveda, 2021) and spillovers in rent control (Sims, 2007; Autor et al., 2014). Our primary contribution is to empirically analyze price controls in the presence of both market power and choice frictions. We show that the interaction between these two market failures is crucial to understanding the impact of price controls on market outcomes and welfare in an important real-world setting.

Second, our paper contributes to the research on pharmaceutical regulation (e.g., Danzon and Chao, 2000; Maini and Pammolli, 2020; Atal et al., 2022; Dubois et al., 2022). We provide novel evidence on the impact of price controls, which are commonly used in practice but have not been empirically analyzed in the literature. We also provide a systematic comparison of price controls and other commonly used policies. More narrowly, existing studies related to cross-brand substitution assume choice frictions or provide (often wide) bounds of welfare effects under different interpretations of brand preferences (Song and Barthold, 2018; Carrera and Villas-Boas, 2023; Kortelainen et al., 2023; Atal et al., 2024; Cao et al., 2024). We are the first to directly measure and incorporate choice frictions in our policy evaluation.

Finally, we build on several recent studies that have documented the immediate short-term effects of India's price control policies before 2015 (Mohapatra and Chatterjee, 2015; Dean, 2019; Jaikumar et al., 2023). We present the first formal welfare analysis of the Indian policy and evaluations of alternative policy designs. Our updated evidence incorporates a richer set of market outcomes over a longer time horizon and adds empirical estimates of choice frictions. Our novel empirical evidence on choice frictions is also related to the broader literature on brand preferences, which has focused primarily on high-income countries (e.g., Bronnenberg et al., 2015). Our results shed light on the distinct nature of brand preferences in low- and middle-income countries (LMICs), where quality regulation is weaker and consumers may face distinct choice frictions.

The remainder of the paper proceeds as follows. We present the setting and data in Section 2 and our model in Section 3. In Sections 4 and 5, we document key empirical facts about the effects of the Indian policy and choice frictions, respectively. We discuss model estimation and results in Section 6 and evaluate the welfare effects of different policies in Section 7.

2 Setting and Data

2.1 The Indian Pharmaceutical Market

The setting for our research is the Indian pharmaceutical industry, which serves more than 1.5 billion people and ranks as the world's third largest pharmaceutical market by volume.

India is also one of the largest pharmaceutical manufacturers, supplying the entire domestic market and 20% of the global generic drug market (by volume), including 45% of the generic drugs consumed in the United States (Indian Brand Equity Foundation, 2024).

We define *therapeutic markets* for medications according to the fourth level of the World Health Organization (WHO) Anatomical Therapeutic and Chemical classification (ATC-4).[4] An ATC-4 group is composed of one or more *molecules* that treat the same conditions and possess comparable biochemical characteristics. A molecule can be available in multiple doses, and we refer to a molecule–dose combination as a *drug*. A *brand* is a distinct proprietary brand name used by manufacturers to sell their version of a drug. For example, Ramipril and Enalapril are two molecules in the ACE inhibitor therapeutic market (C09A). Cardace and Ziram are two brands of the drug Ramipril-2.5mg sold by the manufacturers Sanofi and FDC, respectively.

India is home to more than 1,000 pharmaceutical manufacturing firms. Broadly, these firms can be classified into three groups: multinational companies, Indian national companies, and Indian regional companies. Multinational companies are subsidiaries of global pharmaceutical firms, such as Sanofi and Pfizer. On average, these firms manufacture 34 molecules and supply products in all Indian states. Approximately 90% of these companies also sell at least one molecule in the US. The average Indian national company produces 56 molecules and also supplies the entire Indian market. A third of them also export at least one molecule to the US. In contrast, the average regional firm sells six molecules in five Indian states, does not export to the US, and generates significantly lower revenues than multinational and national companies (Supplementary Table E1).

On average, there are 15 manufacturers for each drug: 1 multinational, 4 regional, and 10 national companies (Supplementary Figure E4). Approximately 97% of manufacturers, including small regional firms, sell their products under a brand name (Supplementary Figure E5). Unlike many other countries, there are almost no unbranded generic versions of a drug sold under its molecule name.

Insurance coverage for pharmaceutical costs in India is minimal, despite these costs forming a significant part of healthcare expenses. In 2014–2015, approximately 80% of households had no insurance coverage. Furthermore, most insurance plans do not cover drug costs, resulting in 95% of households paying for all their medications out of pocket (Government of India, 2015). The burden of pharmaceutical costs is large: 70% of all outpatient expenditures are on pharmaceuticals (Government of India, 2015).

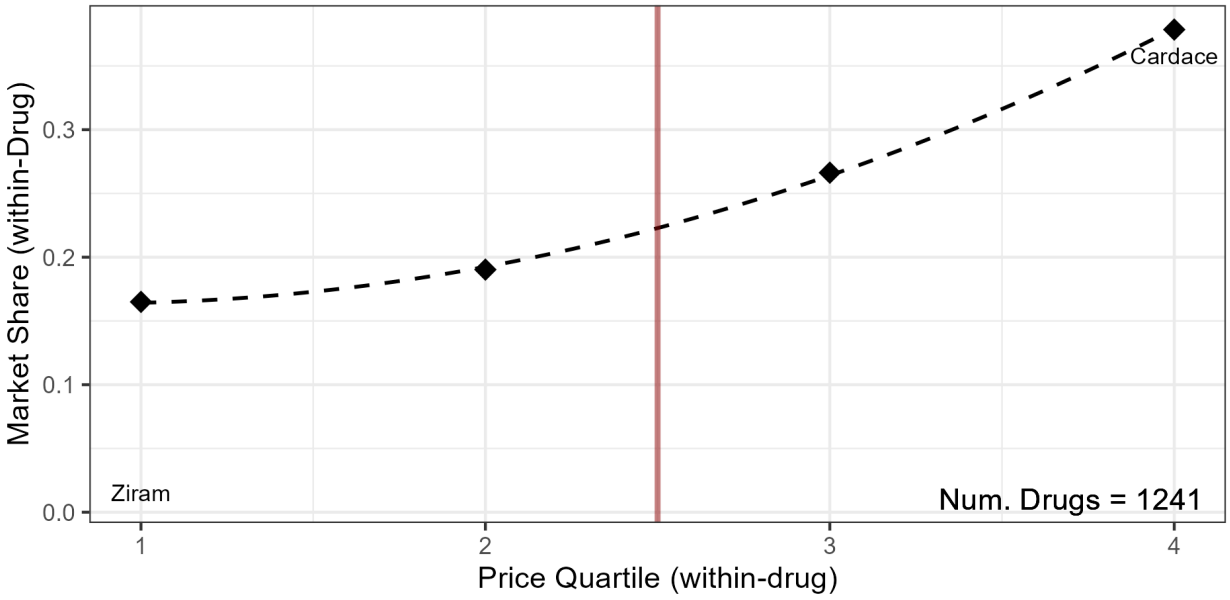
Consumers typically purchase pharmaceutical products from private retail pharmacies.[5]

[4] ATC-4 groups are commonly used by researchers and policymakers to define markets.

[5] In some rural settings and public health care facilities, physicians directly dispense drugs to patients.

Most pharmacies in India are small, independent "mom-and-pop" operations. Physicians typically prescribe specific brand names (Supplementary Figure F3), and by law, pharmacies are required to dispense the product exactly as prescribed, including the specified brand name; no substitution of any form is permitted.[6]

Figure 1: Relationship Between Prices and Market Share in 2012



Notes: The figure presents the price quartile across brands of the same drug on the x-axis and the within-drug market share on the y-axis. Each observation is a product. We divide all brands of drugs into quartiles based on price in 2012. The fourth quartile represents the most expensive brand, while the first quartile represents the cheapest brand. We then compute the aggregate market share all brands in each quartile across N drugs. The market share of a given product is the ratio of the sale of that product to the total sales of that drug. For illustration, the brands Cardace and Ziram for Ramipril-2.5mg are labeled. The vertical line illustrates the price ceiling under the Indian policy.

Brand Preferences and Quality Consumers in India exhibit strong brand preferences. In Figure 1, we show that certain expensive brands have a larger market share than cheaper brands of the same drug, suggesting that consumers are willing to pay a premium for these brands.

In India, brand preferences may reflect actual differences in quality, as weak regulation fails to filter out substandard products. Quality may vary between brands because of input

These drugs account for less than 10% of the market (Ministry of Health & Family Welfare, 2015-2016).

[6]Specifically, Drugs Rule 65 (11A) stipulates that pharmacists are not allowed to "supply any other preparation, whether containing the same substance or not." While there are reports of pharmacists dispensing drugs without prescriptions (Saradamma et al., 2000; Basak and Sathyanarayana, 2012), this behavior is beyond the scope of the present paper.

quality, manufacturing practices, transportation, and storage. Before 2017, licenses to manufacture a new brand of an existing drug were granted based on visual inspections rather than clinical bioequivalence tests, a more rigorous standard that has been in place in the US and most European countries since at least the 1990s.[7] Furthermore, there are widespread concerns about the reliability of government inspections.

A recent policy episode prominently highlights these quality concerns in India.[8] In August 2023, regulators proposed a policy that would require physicians to prescribe drugs using generic rather than brand names. The policy was heavily criticized by the Indian Medical Association, which explicitly requested that the policy "be deferred until the government can assure the quality of all drugs manufactured in India" (Malhotra, 2023). The policy proposal was subsequently withdrawn.

Brand preferences could also reflect choice frictions, such as misinformation and agency issues. Patients may not be aware that two brands contain the same molecule, and physicians may lack knowledge of cheaper alternatives, as has shown to be the case in the US and Europe (Bronnenberg et al., 2015; Qu et al., 2022; Arrow et al., 2020). In addition, physicians may choose not to prescribe high-quality, inexpensive brands because of financial incentives from pharmaceutical firms (Narendran and Narendranathan, 2013).

2.2 Price Control Policy

Our empirical analysis focuses on a policy called the Drug Price Control Order 2013. The DPCO granted Indian regulators the authority to set price ceilings for drugs essential to the health needs of the Indian population.[9] Announced in October 2013, the DPCO set price ceilings for 550 drugs between 2013 and 2014. The set of drugs under price controls was expanded to 870 in 2015, covering 20% of the Indian pharmaceutical market by sales revenue. The drugs under price control are more likely to treat common diseases, have high sales, be launched before 2005, and have multiple manufacturers. (See Supplementary Figures E6–E10.)

The price ceiling for each drug was based on pre-policy prices. For drugs with more than five manufacturers, which constitute 90% of regulated drugs, the price ceiling was the unweighted mean price of all brands of the drug with at least 1% market share by volume. For drugs with fewer than five manufacturers, the price ceiling was determined by calculating

[7] See Drugs and Cosmetics Rules, Tenth Amendment, 2017.

[8] See also the Ranbaxy case and heparin case for specific examples of substandard drugs manufactured in India.

[9] Specially, the National Pharmaceutical Pricing Authority, a bureaucratic agency, created the National List of Essential Medicines (NLEM) to specify which drugs were regulated. The NLEM was modeled on the WHO List of Essential Medicines but was modified to meet the local needs of India.

the average reduction for other regulated drugs in similar therapeutic markets (ATC-3) and then applying this average decrease to the pre-policy price of the focal drug. Unless the price controls were removed for a drug, its price caps remained in effect. The price ceilings are revised once a year to adjust for government-determined inflation.

The DPCO also empowered the regulators to set price ceilings for additional drugs in the future, including patented drugs. After the 2015 expansion, the set of regulated drugs remained unchanged through the end of our study period in 2019.[10] An amendment in 2019 exempted all patented drugs from price controls for five years.

The DPCO 2013 was a substantial expansion in Indian price control policy. Before the DPCO 2013, only 95 drugs were subject to price controls under a 1995 law. After India began enforcing pharmaceutical patents in 2005 (Sampat and Shadlen, 2015), concerns about rising drug prices led to years of deliberation on price control policies. Although the eventual implementation of pharmaceutical price controls was widely expected, the precise timing, the specific drugs to be regulated, and the method of setting the price ceilings were largely unanticipated.

Going forward, we refer to the DPCO as "the Indian policy" to simplify exposition.

2.3 Data

Our primary dataset is the All India Organization of Chemists and Druggists (AIOCD) dataset, which provides monthly information on drug prices and sales for every state in India between January 2010 and December 2019. This dataset has been used both in academic research (Dean, 2019; Mohapatra and Chatterjee, 2015; Cao and Chatterjee, 2022) and extensively by the Indian government for pharmaceutical regulation.[11] The AIOCD data are ideal for studying the Indian policy since regulators set price ceilings based on information in this data.

The AIOCD collects information on sales and prices from a panel of 12,000 stockists—intermediaries between pharmaceutical companies and private retail pharmacists—covering nearly the entire universe of drug sales in private pharmacies in India.[12] We observe sales and prices at the level of a stockkeeping unit (SKU), which is a combination of brand, molecule, dosage, and package size. For simplicity, we convert all variables to a per-pill unit and aggregate them to the brand–molecule–dose level.

[10] An update in October 2022 added price controls for 34 drugs and removed them for 24 drugs.

[11] See, for example, the 2019–2020 annual report by the Department of Pharmaceuticals.

[12] The dataset does not include drug sales in public pharmacies or public health facilities. The role of these outlets in India is limited: 85% to 90% of all drug sales occur in private pharmacies (Ministry of Health & Family Welfare, 2015-2016).

For our structural analysis, we further transform the units of measurement from a pill to the defined daily dose (DDD). The DDD represents the average maintenance dose per day for a molecule in adults, and using DDD as the unit of analysis allows us to effectively measure cross-molecule and cross-dosage substitution, as is common in the literature.[13]

We conducted an online survey of physicians to measure choice frictions. We also conducted small field surveys of consumers and pharmacists to investigate how choices vary with consumer characteristics and pharmacist knowledge. We defer detailed discussion of these surveys to Section 5.1.

We also use several supplementary data sources. We manually extracted data on the set of regulated drugs and their price ceilings from announcements on the Indian regulators' website. We used the National Sample Survey: Health 2014–2015 (NSS Health) to obtain information on the distribution of healthcare expenditures, insurance coverage, and educational attainment (Government of India, 2015). The Longitudinal Aging Survey of India (LASI) provides microdata on the income, treatments, and expenditures of individuals with various diseases. The Pharmaprojects dataset from Pharma Intelligence provides timelines for drug development and drug launches. See Supplementary Section A.2 for additional information on these data sources.

3 Model

In this section, we introduce our framework for analyzing price controls. We begin with a high-level overview, followed by a formal discussion of the model. At the end of the section, we illustrate the key insights with a stylized example. We take the model to data in Section 6.

Consumers with different price sensitivities choose a pharmaceutical product based on perceived product utility and price from a discrete choice set. Frictions may create a wedge between the true utility and the utility that drives choices.

In equilibrium, firms may mark up their prices because of product differentiation and limited competition. Firms producing high-utility products find it profitable to mark up prices and target price-insensitive consumers. These markups distort the choices of price-sensitive consumers who would buy high-utility products at cost but not at the equilibrium prices.

Price controls constrain markups and bring prices closer to cost. This price change affects welfare through two channels. First, lower prices redistribute welfare from firms to

[13]For example, four metformin-500mg pills are equivalent to one evogliptin-5mg pill because the DDD of metformin is 2000 mg and that of evogliptin is 5 mg.

inframarginal consumers. Second, marginal consumers switch to the now-cheaper products because these consumers perceive a welfare gain. If there are no choice frictions, this substitution improves consumer surplus and overall welfare by correcting monopoly distortions. However, if choice frictions cause consumers to overvalue the regulated products, the realized gains are smaller than the perceived gains from switching. When choice frictions are sufficiently large, lower prices can *reduce* consumer welfare.

In addition to affecting prices, price controls may influence a firm's decision to supply the market. A sufficiently low price ceiling induces firms to exit, reducing both profits and consumer surplus. If costs are correlated with product utility and there are limited choice frictions, then the most valued products are the first to exit, implying a greater welfare loss.

3.1 Consumer Preferences and Choice Frictions

3.1.1 Consumer Preferences

A consumer i in state s during year t chooses a product j from a set J_{st}. A product is a combination of a brand, dose, and molecule, and J_{st} consists of all products in the same therapeutic markets, defined by ATC-4 group.[14] The set of products is partitioned into mutually exclusive and jointly exhaustive groups based on the molecule $m(j)$. For example, Cardace-Ramipril-5mg belongs to the Ramipril group. The outside option is denoted by $j = 0$.

A consumer chooses one product to maximize utility,[15] as specified by the following random coefficient nested logit model (Berry et al., 1995):

$$U_{ijst} = \underbrace{\delta_{js}}_{\text{Product Utility}} + \underbrace{\xi_{jst}}_{\text{Unobs. Shocks}} + \underbrace{\zeta_{im(j)st} + (1-\rho)\,\epsilon_{ijst}}_{\text{Idiosyncratic Shocks}} - \underbrace{\alpha_i p_{jst}}_{\text{Price Sensitivity}} . \tag{3.1}$$

The term δ_{js} represents the mean time-invariant utility that a consumer expects to receive from consuming product j in state s. Product utility changes over time because of market-level shocks ξ_{jst} that are observable to consumers and firms but not to the researcher.

Consumer preferences also vary because of idiosyncratic shocks, which consist of two components: a molecule-level shock $\zeta_{im(j)st}$ and a product-level shock ϵ_{ijst}. We assume that ϵ_{ijst} is i.i.d. type-1 extreme value and $\zeta_{im(j)st}$ is distributed such that $\zeta_{im(j)st} + (1-\rho)\,\epsilon_{ijst}$ is

[14] Products in the same ATC-4 group treat the same disease with similar therapeutic characteristics and are commonly used to define markets in the pharmaceutical literature.

[15] In our model, we consider a unitary "consumer" representing the joint decision made by patients and physicians, as is common in the health economics literature. In Supplementary Section D.2, we formulate an extended model of patient and physician choices and show that this abstraction is with limited loss for our analysis.

also i.i.d. type-1 extreme value, yielding the nested logit model (Cardell, 1997; Berry, 1994). The molecule-level shocks capture heterogeneous match effects with different treatments. For example, patients may have different preferences for a particular molecule because of differences in comorbidities. The product-level shocks capture idiosyncratic factors such as availability in a consumer's local pharmacy. The parameter $\rho \in [0, 1]$ captures the importance of the molecule-level shock relative to the product-level shock and thus governs the substitutability across molecules. A higher ρ implies that consumers are less likely to switch across molecules.

Consumers trade off the utility of a product with its prices p_{jst}, depending on their price sensitivity α_i. We assume that price sensitivity depends on a consumer's income y_i and health status $\theta_i \in \{poor, good\}$, such that $\alpha_i = \frac{\alpha_{\theta_i}}{y_i}$. In Supplementary Section D.1, we derive this specification from a microfounded model where consumers choose a product to maximize Cobb–Douglas utility over health and nonhealth consumption subject to a budget constraint. The joint distribution of income and health status among consumers is denoted by $F_s(\theta_i, y_i)$, and the distribution of price sensitivity is denoted by $H_s(\alpha_i)$.

Under this setup, the market share of a given product σ_{jst} is

$$\sigma_{jst} = \int \underbrace{\frac{\exp(\frac{\delta_{js} - \alpha_i p_{jst}) + \xi_{jst}}{1-\rho})}{\exp(\frac{I_{imst}}{1-\rho})}}_{\sigma_{ijst|m}} \underbrace{\frac{\exp(I_{imst})}{\exp(I_{ist})}}_{\sigma_{imst}} dH_s(\alpha_i), \tag{3.2}$$

where $I_{imst} = (1-\rho) \log \sum_{k:m(k)=m} \exp(\frac{\delta_{ks} - \alpha_i p_{kst}}{1-\rho})$ is the inclusive value of the molecule m and $I_{ist} = \log \sum_{m=0}^{M_{st}} \exp(I_{imst})$ is the inclusive value of the market (McFadden, 1977). These inclusive values I_{imst} and I_{ist} capture the total value of all the products of a given molecule and across all the molecules in the market, respectively.

Under revealed preference, consumer welfare is captured by the inclusive value of the market I_{ist} (Small and Rosen, 1981). This inclusive value is the utility that a consumer i expects to receive in a market consisting of products J_{st} with product utility and prices (δ, p).

3.1.2 Choice Frictions

Consumers may not choose the brands that provide them with the highest utility because of choice frictions. As discussed in Section 2.1, choice frictions arise from two main factors: mistaken beliefs and agency issues. Consumers and possibly some uniformed healthcare providers may have mistaken beliefs about the quality of different brands (Bronnenberg et al., 2015; Das and Hammer, 2014). Providers may not know of some cheaper alternatives (Arrow et al., 2020). Financial incentives, such as detailing, can also lead physicians to

prescribe high-priced brands at their patients' expense (Narendran and Narendranathan, 2013; Iizuka, 2012).

We model these choice frictions *as if* they alter a product's mean utility δ_{js}. Specifically, we assume that $\delta_{js} = \delta_{js}^{\text{true}} + \delta_{js}^{\text{fr}}$, where δ_{js}^{fr} represents the aforementioned choice frictions and $\delta_{js}^{\text{true}}$ represents the true utility, which captures welfare-relevant factors such as safety, efficacy, and availability in pharmacies. By choosing products based on δ_{js} instead of $\delta_{js}^{\text{true}}$, consumers systematically deviate from their optimal choices. Our formulation abstracts from the specific mechanisms underlying choice frictions. We emphasize that we are not literally assuming that consumers have mistaken beliefs. Rather, we are parsimoniously and compositely capturing all wedges that prevent consumers from choosing the product with the highest utility, which suffices for the primary purposes of this paper.

The objective of this paper is to document how price regulation affects choices and whether any changes in choices are *welfare improving*. For this purpose, it is sufficient to capture the wedge between actual choices and the choices that would be made without frictions; we do not need to identify the specific drivers of this wedge. For illustration, in Supplementary Section D.2, we derive our formulation from a richer model in which patients and physicians make joint treatment choices based on their (potentially inaccurate) beliefs and distortionary financial incentives, elucidating the link between richer models and our formulation.[16]

Welfare with Choice Frictions When there is a wedge between how consumers choose and the true benefits, the standard revealed preference measure of welfare is inaccurate. We account for these choice frictions by directly measuring them and then adjusting for the wedge between choice utility and welfare-relevant true utility. As shown in Allcott (2013) and Train (2015), the appropriate measure of consumer surplus is $I_{ist}(\delta, p) - \sigma_{ist}\delta^{\text{fr}}$, where σ_{ist} and δ^{fr} denote the vector of choice probabilities and choice frictions, respectively. This measure is the expected utility when consumers choose according to δ, but welfare is evaluated according to δ^{true}. The change in consumer surplus from a price change to p^{pol} is:

$$\Delta CS_{ist} = \underbrace{I_{ist}(p^{\text{pol}}) - I_{ist}(p)}_{\text{Revealed Preference Welfare}} \underbrace{- \left[\sigma_{ist}(p^{\text{pol}}) - \sigma_{ist}(p)\right] \delta_s^{\text{fr}}}_{\text{Adjustment for Frictions}}. \tag{3.3}$$

Failure to account for choice frictions can lead to misleading conclusions about the sign and magnitude of the welfare gains from a price control policy. Consider the case where the

[16] Our model also assumes that choice frictions do not vary between consumers. Extending the model to allow for heterogeneity in choice frictions as random effects does not influence aggregate market-level welfare but does alter the distribution of welfare. We focus on market-level outcomes in our analysis and defer research on distributional impacts to future work.

price of a product j decreases and a consumer switches to j in response to the policy. In the absence of choice frictions, the welfare of this marginal consumer increases by revealed preference. However, if this consumer overvalues this product in the first place because of choice frictions $\delta_{js}^{\text{fr}} > 0$, the true welfare gain is smaller. If the choice frictions are sufficiently large, consumer welfare can *decrease* because of a price decrease.

3.2 Firm Pricing and Exit

We model the supply side as a static two-period sequential game. In the first period, firms decide whether to discontinue a subset of their products based on anticipated profits in the second period. In the second period, profit-maximizing firms compete in prices à la Nash–Bertrand, given consumer preferences, their marginal costs, and the set of products on the market. The regulator may set a price ceiling, which could induce both price changes and product exits.

We assume that firms make pricing and exit decisions annually and separately for each state s. For simpler exposition, we suppress the state s and year t subscripts. We start by discussing the pricing game in the second period.

3.2.1 Firm Pricing

Given consumer preferences and the set of products on the market J, firms compete in prices à la Nash–Bertand. Specifically, firm f sets prices to maximize profits across its product portfolio, denoted by J_f, given the prices of its rivals $\max_{p_j \forall j \in J_f} \Pi_f = \sum_{j \in J_f} (p_j - mc_j)\sigma_j(p)$, where p denotes the vector of all prices, mc_j denotes the marginal cost of product j, and $\sigma_j(p)$ denotes the market share of product j, as formulated in Equation 3.2.

Absent price controls, the market equilibrium is a vector of prices p^{eq} such that the first-order conditions for all products are satisfied, as specified in matrix form in Equation 3.4 below:

$$\sigma(p^{\text{eq}}) - \Omega(p^{\text{eq}} - mc) = 0, \tag{3.4}$$

where $\Omega_{jj'} = 1\{\exists f : j \in J_f \text{ and } j' \in J_f\} \frac{\partial \sigma_j(p^{\text{eq}})}{\partial p_{j'}^{\text{eq}}}$.

In our policy analysis, firms must comply with price ceilings that restrict profit maximization. Let $\bar{p}_j$ denote the price ceiling and λ_j denote the Lagrangian multiplier for product j. The equilibrium prices given a policy, p^{pol}, are characterized by the following conditions:

$$\sigma(p^{\text{pol}}) - \Omega(p^{\text{pol}} - mc) = \lambda \text{ (First Order Conditions)}$$
$$\lambda(p^{\text{pol}} - \bar{p}) = 0 \text{ (Complementary Slackness).}$$

Note that prices change because of two forces. First, the price ceilings will be binding for certain brands $p^{\text{eq}} > \bar{p}$, forcing lower prices because of the complementary slackness condition. Second, prices for products below the ceiling or without a ceiling may also change in response to price changes from competitors.

3.2.2 Product Exit

A firm f is endowed with a set of products $\mathcal{J}_f$ that it can produce.[17] The firm chooses a subset of these products $J_f \in P(\mathcal{J}_f)$ to supply in the market by removing the products in $\mathcal{J}_f \setminus J_j$, where $P(\mathcal{J}_f)$ denotes the power set of $\mathcal{J}_f$.

The firm chooses J_f to maximize the expected second-period profits, which depend on consumer preferences, the products offered by other firms J_{-f}, and the price ceiling $\bar{p}$:

$$J_f^*(J_{-f}) = \arg \max_{J_f \in P(\mathcal{J}_f)} \sum_{j \in J_f} (p_j^* - mc_j)\sigma_j(p^*)$$

where $p^*(J_{-f}, mc, \bar{p})$ are the equilibrium prices in the second period.

Firms make product exit decisions simultaneously with complete information about their rivals' marginal costs and profit functions. An equilibrium is a set of product offerings J^{eq} that satisfy the condition $J^*(J_{-f}^{\text{eq}}) = J_f^{\text{eq}} \, \forall f$. Price controls potentially induce product exit by lowering expected profits. Although multiple equilibria are theoretically possible, we find a unique equilibrium in our analysis. See Section 7 and Supplementary G.4 for further details on our checks for multiple equilibria.

We assume that there are no fixed costs or scrap values. This assumption is motivated by the fact that most products in our analysis were launched more than 10 years ago and therefore most fixed costs have already been amortized. Typically, fixed costs are included in the model to help rationalize observed exits. We show that the exits predicted by our model align with the observed exits, validating that our model fits the data well despite this restriction.

[17] Conceptually, these are the products that the firm has already launched in an unmodeled period 0.

3.2.3 Discussion of Other Supply-Side Margins

We do not model the entries of new brands because they are not empirically relevant in our context. New-brand entries were rare before the policy, and we show in Section 4.4 that entries did not change significantly because of the policy. We also do not model how price controls influence the launch of new molecules in the future given the limited changes we find in Section 4.5.

We also do not endogenize quality δ_j^{true} or marginal costs mc_j. While one may be concerned about firms reducing quality to cut costs after price controls, we observe that the Indian policy primarily targets high-priced brands, the manufacturers of which often export to other countries such as the US, where quality regulations are more stringent. Reducing quality can jeopardize profits from these lucrative export markets. Furthermore, firms are discouraged from reducing quality, as the Indian government has become more stringent: a bioequivalence standard was introduced in 2017, regular inspections of manufacturing facilities have increased, and licenses for substandard manufacturers have recently been revoked. More than 75% of the physicians in our survey report that the quality of pharmaceutical products was the same after the Indian policy, supporting our assumption (Supplementary Figure F4).

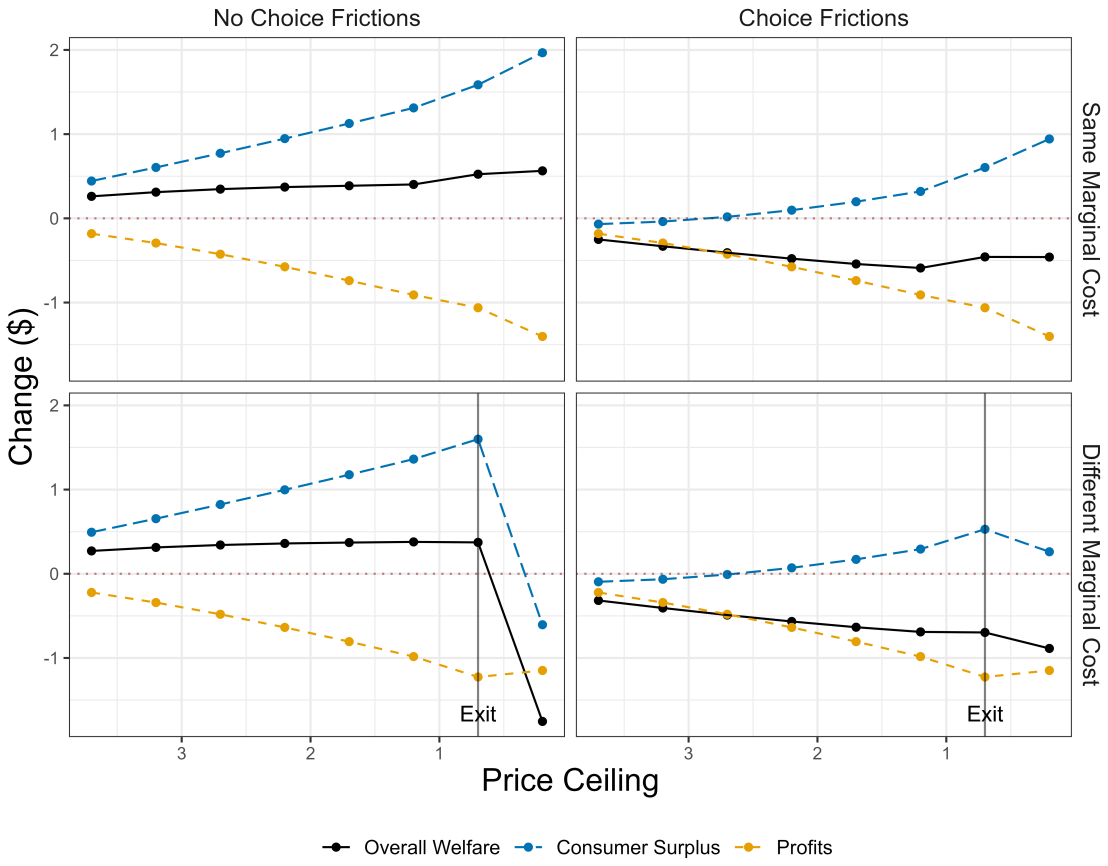
3.3 Stylized Illustration: Welfare Effects of Price Controls

We present a stylized example to illustrate the key economic insights. Let there be two types of consumers: price sensitive ($\alpha_i = 8$) and price insensitive ($\alpha_i = 0.5$), with the former making up 60% of the market. The market consists of one *h*igh brand and three *l*ow brands produced by different firms. Let $\delta_l = \delta_l^{\text{true}} = 0$ and $mc_l = 0$ for all low brands. Consumers perceive the utility of the high brand as $\delta_h = 4 = \delta_h^{\text{true}} + \delta_h^{\text{fr}}$. The marginal cost of the high brand mc_h and choice frictions $\delta_h^{\text{fr}} = 4 - \delta_h^{\text{true}}$ are free parameters.

Firms can mark up prices $p_j^{\text{eq}} > mc_j$ because of product differentiation and limited competition. The brand h distinguishes itself from brands l because of its higher perceived utility, and the lack of other high-utility options gives h market power, which in equilibrium allows it to mark up its price.

We illustrate the effect of a price ceiling $0 < \overline{p} < p_h^{\text{eq}}$ for four cases with different assumptions about marginal cost mc_h and choice friction δ_h^{fr}. In the first case, brand h has higher true utility, and all brands have the same cost ($\delta_h^{\text{fr}} = 0, mc_h = 0$). In the second case, there are no true quality differences, and consumers' preference for brand h is entirely due to choice frictions ($\delta_h^{\text{fr}} = 4, mc_h = 0$). In the third and fourth cases, brand h has a higher cost with true quality differences ($\delta_h^{\text{fr}} = 0, mc_h = 0.5$) and without true quality differences

Figure 2: Stylized Illustration of the Welfare Effects of Price Controls with Market Failures



Notes: The figure presents a price ceiling on the x-axis and the change in welfare due to that price ceiling relative to the market equilibrium in money metric units ($). The different components of welfare—consumer surplus, profits, and net welfare—are presented in separate colors. The panels show different illustrative cases defined in the main text.

$(\delta_h^{\text{fr}} = 4, mc_h = 0.5)$, respectively.

In Figure 2, we plot the changes in consumer surplus, profits, and social welfare at different levels of price ceilings relative to the free-pricing baseline for each of the four cases.

Case 1 In the first case, the price ceiling statutorily lowers the price of h and, in equilibrium, also lowers the price of l but does not induce the exit of any product. Most price-insensitive consumers continue to choose brand h and experience a welfare improvement due to the lower prices. This welfare improvement is exactly offset by the loss in profits, implying a transfer of welfare from firms to these inframarginal consumers. The price ceiling also induces some price-sensitive consumers to switch from l to h.[18] In the absence of choice

[18]Formally, with logit errors in the model, a small share of price-insensitive consumers will also switch, but for simplicity, we discuss the example as if only price-sensitive consumers switch.

frictions, these marginal consumers are better off by revealed preference. In this case, the price ceilings correct the distortions due to market power. Total social welfare increases as the price ceiling is lowered (top-left panel of Figure 2).

Case 2 In the second case, all the products have the same true quality, although consumers perceive h to be better. The effects of the price ceilings on positive outcomes such as prices, sales, and product exit are identical to those in Case 1. The key difference lies in the welfare effects for marginal consumers. While marginal consumers perceive a surplus gain from switching (hence their decision to switch), the actual surplus gain is smaller and often becomes *negative* because of choice frictions. For a range of price ceilings, this welfare loss for marginal consumers is large enough to outweigh the welfare gains for inframarginal consumers, resulting in a net negative effect on consumer surplus (top-right panel of Figure 2). The consumer gains are outweighed by profit losses, and total welfare decreases for any price ceiling. A key observation is that distortions from market power and choice frictions counteract each other in equilibrium: High prices act as a "corrective tax" that deters consumers from choosing the overvalued products. By attempting to correct one market failure, price controls inadvertently exacerbate the adverse impacts of the other.

Case 3 In the third case, brand h has higher true quality and is costlier to produce. High equilibrium prices reflect the cost of providing a truly high-quality product. The effect of a price ceiling above mc_h is the same as in Case 1. However, a price ceiling below mc_h would force h to exit. The exit of a high-quality product reduces profits, consumer surplus, and overall welfare, as shown in the bottom-left panel of Figure 2.

Case 4 Last, we consider a case where h is costlier to produce but has the same true quality as l. As in Case 3, a stringent price ceiling induces h to exit, but this exit has little impact on consumer surplus because of the availability of other products of similar quality. In fact, such an exit *improves* surplus for some consumers, as it prevents them from paying more for an overvalued product. In our example, total welfare declines because of the loss of profits from h.

This simple example shows that the welfare effects of a price ceiling depend on three key economic primitives: markups, choice frictions, and the relationship between true product utility and marginal cost.

4 Effect of the Indian Policy on Market Outcomes

4.1 Empirical Strategy

We estimate the effect of the Indian policy on key market outcomes using an event study design. Intuitively, we compare the differential changes in outcomes for regulated products relative to those of unregulated products following the implementation of the policy. A treated unit is a regulated product, which we further classify as "Above Price Ceiling" or "Below Price Ceiling" based on the pre-policy prices. A control unit is a product not regulated by the Indian policy and not in the same ATC-4 group as any regulated product. We exclude unregulated products within the same ATC-4 group as a regulated product because of potential equilibrium effects. In Supplementary Table E2, we present descriptive statistics by regulation status.

We use the event study methodology proposed by Sun and Abraham (2021) and estimate the average treatment effect on the treated (ATT) with the following regression specification:

$$Y_{jst} = \sum_{G} \sum_{k=-4}^{7} \delta_k^G 1\left\{T_j - t = k, G_{js} = G\right\} + \alpha_{js} + \gamma_{st} + \epsilon_{jst}\,, \tag{4.1}$$

where, for product j, in state s during a 6-month period t, Y_{jst} is the outcome of interest, $T_j \in \{2013, 2015\}$ is the year in which the product was put under price control, α_{js} is a product–state fixed effect, and γ_{st} is a state–year fixed effect. The variable $G_{js} \in \{\text{Above}, \text{Below}\}$ indicates whether a product is above or below the price ceiling. Standard errors are clustered at the product level.

The key identification assumptions are (1) parallel trends in the absence of price controls and (2) no anticipatory effects. We will directly evaluate assumption (1) by checking for pretrends in our estimates. We first present evidence in support of assumption (2).

No Anticipatory Effects For firms to have strategically responded in anticipation of the Indian policy, they would need to have known which drugs would be subject to price control, when the price controls would be implemented, and how the price ceilings would be set. Since the Indian policy was extensively discussed in parliament and by media outlets, firms likely knew that price controls of some form were forthcoming. However, the method of setting the price ceiling at the mean price of all brands was unexpected, as previous price ceilings had been set based on the government's estimates of production costs. Thus, firms had limited ability to respond strategically in anticipation of the policy.

To empirically evaluate this assumption, we conduct a placebo exercise. For each month in our panel, we simulate the price ceiling based on drug prices in that month. If firms

were strategically manipulating prices to increase the price ceiling, we would expect to see an increase in the simulated price ceiling for the treated drugs before the policy was implemented. In Supplementary Figure E19, we show that there is no systematic trend in the simulated price ceiling for regulated drugs before the Indian policy, indicating that firms were not strategically changing their prices in anticipation.

4.2 Results: Prices and Sales

In Figure 3a, we present our estimates of the effect of the Indian policy on (log) prices. There are no statistically significant or economically meaningful pretrends in prices, validating our parallel trends assumption.[19] After the policy was gradually implemented, the prices of regulated products above the price ceiling began to decline. Two years after the policy was announced, prices had decreased by approximately 25%, which corresponds to the expected price drop if firms adhered to the price ceilings. Subsequently, prices decreased even further and exceeded this statutory benchmark. The prices of products below the price ceiling also decreased by approximately 5%. The decline in prices beyond the statutory requirement suggests that competition amplified the effect of the price regulation.

In Figure 3b, we examine the relationship between price changes and pre-policy price *levels*. Across different brands of the same drug, we find that the price changes were monotonically decreasing across within-drug price deciles: the most expensive brands experienced the largest price declines. These results show that the policy generated rich variation in price changes based on pre-policy price levels.

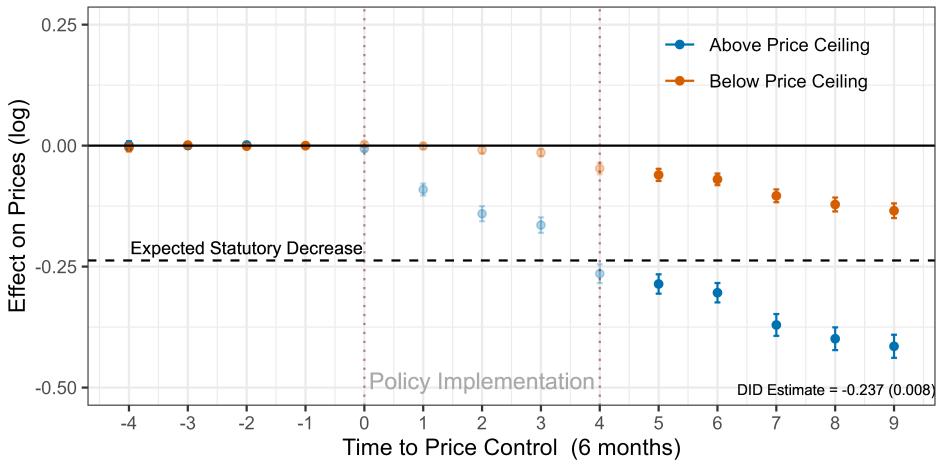
In Figure 4a, we show that the sales of regulated products above the price ceiling increased by 36%. The sales of regulated brands below the ceiling did not change. We note that there is a negative pretrend in sales for regulated products below the price ceiling. If the pretrend had continued post-policy, our estimates would be downward biased. In Supplementary Figure E21, we show that the increases in sales are highest for the brands with the highest pre-policy prices.

4.3 Results: Market Expansion and Cross-Drug Substitutions

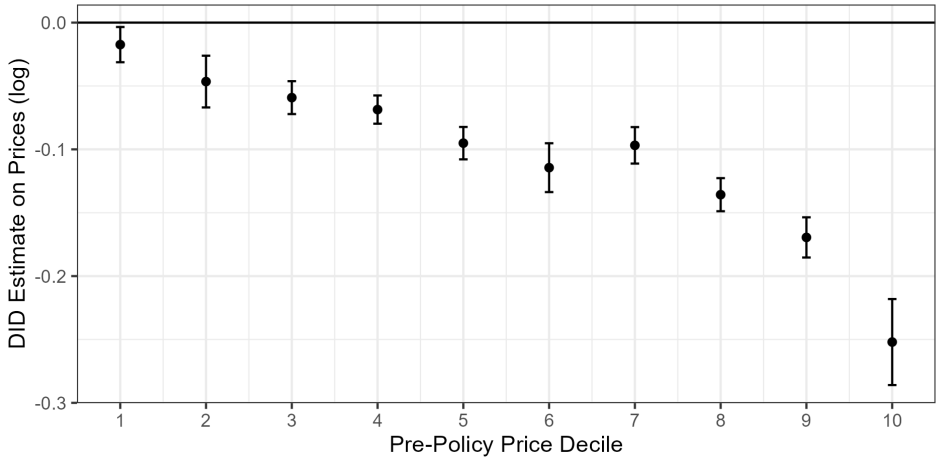
Next, we examine whether the policy led to changes in drug-level outcomes. Recall that the regulated drugs are considered the most effective in their therapeutic markets. The policy would be particularly beneficial if it allows more consumers to access these essential

[19] The pretrends are estimated and are *not* mechanically set to zero, as the figure may suggest. The figure includes error bars for the pretrends, but they are not visually discernible.

Figure 3: Effect of the Indian Policy on Prices



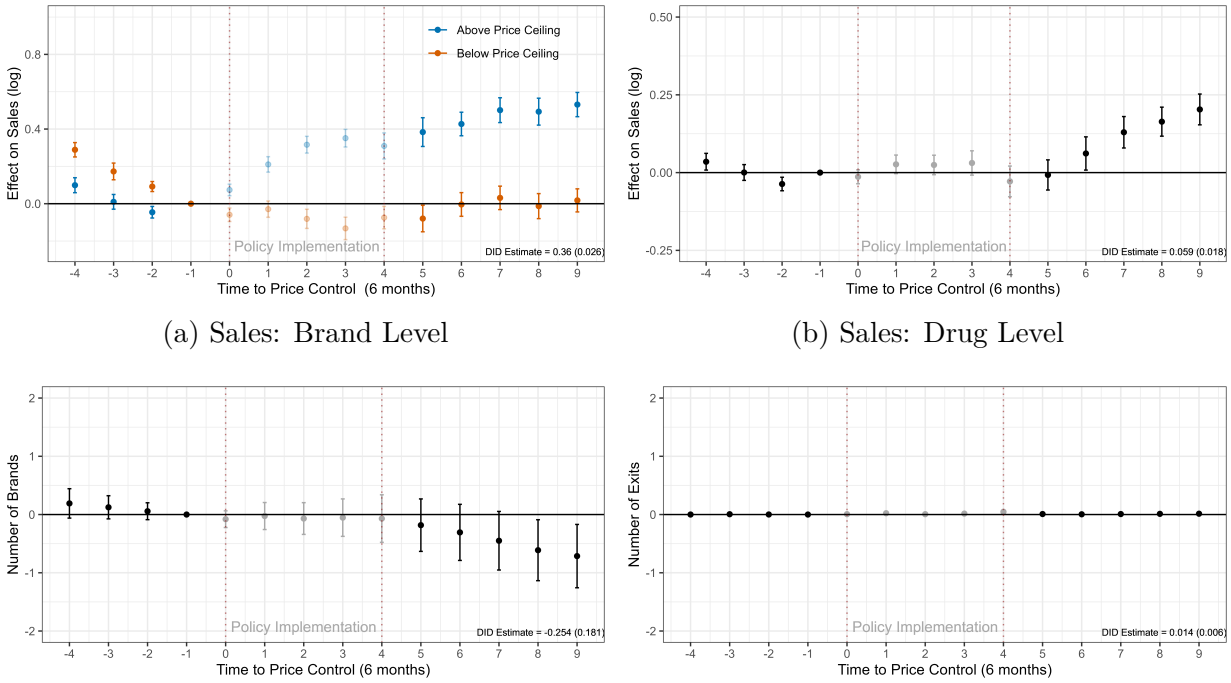
(a) Event Study Estimates



(b) Difference-in-Differences Estimates by Pre-Policy Price Levels

Notes: Panel (A) presents the dynamic effects of the price control policy on prices. The x-axis is the time from when the price control was implemented (in 6-month intervals). The y-axis shows the ATT estimates with 95% confidence intervals. Estimates are presented separately for products above and below the price ceiling. Panel (B) presents the difference-in-differences estimate of the effect of the Indian policy on prices (log) for different price deciles in 2012. The x-axis denotes the decile of price premia in 2012, and the y-axis denotes the difference-in-differences point estimate and 95% confidence intervals. The standard errors are clustered at the product level.

Figure 4: Effect of the Indian Policy on Sales and Product Availability



(a) Sales: Brand Level

(b) Sales: Drug Level

(c) Number of Brands

(d) Exit of Brands

Notes: The figure presents the dynamic effects of the price control policy on sales for the treated products (Panel (A)), sales for treated drugs (Panel (B)), the number of brand exits per drug (Panel (C)), and the number of brands per drug (Panel (D)). The x-axis is the time from when the price control was implemented (in 6-month intervals). The y-axis shows the ATT estimates with 95% confidence intervals.

medications. For this analysis, we aggregate our sample to the drug level and compare the regulated drugs to the control drugs, using the same event study design.

Sales of the regulated drugs increased by 6% (Figure 4b). We also find a 50% decrease in the sales of drugs not regulated but in the same ATC-4 as at least one regulated drug (Supplementary Figure E22). These results show that price controls led to substitution across treatments and expanded access to essential medicines.

4.4 Results: Exit, Entry, and Detailing

To evaluate changes in product availability, we estimate the effects of the Indian policy on the number of brands per drug. We find that the policy leads to a small reduction of 0.25 brands per regulated drug, corresponding to a decrease of 1.7% (Figure 4c). This reduction is driven by a slight increase in exits (Figure 4d), while we observe no significant changes in the entry of new brands (Supplementary Figure E25). Although the policy had minimal effects on product availability overall, we do observe policy-induced product exits for 17.8% of therapeutic markets (Supplementary Figure E27), which may have significant negative

welfare consequences.

We also estimate the impact of the Indian policy on advertising to physicians ("detailing") to examine how the price controls affect ancillary supply-side margins. We use the IQVIA ChannelDynamics dataset, a leading market intelligence resource, which records monthly detailing expenditures at the firm–molecule–channel level in India.[20] Although there was no change in detailing on the extensive margin (Supplementary Figure E26a), we find a 16% reduction in detailing expenditures for regulated products priced above the ceiling (Supplementary Figure E26b). We note that the average firm spends approximately $6,500 on detailing per drug–year, implying that the change in detailing is a minuscule $1,000. Therefore, despite the substantial percentage change, the impact is minimal because of the low levels of detailing expenditures.[21]

4.5 Results: Effect on New Molecules

Price controls may inhibit the development and diffusion of new drugs, creating a trade-off between short-run affordability and long-run innovation (Bryan and Williams, 2021). While this trade-off is central to the debates about pharmaceutical price controls in high-income countries, it is a priori less important in India and other LMICs that generate only a small share of global pharmaceutical revenue and profits (IMS, 2015). We provide a brief overview of our analysis of this margin. See Supplementary Section E.3 for a complete discussion of the data, estimation procedure, and results.

To empirically verify this trade-off, we estimate the impact of the Indian policy on the launch of new molecules in India and globally. Using the Pharmaprojects dataset, we compare the innovative activities before and after the implementation of the Indian policy for firms that specialize in therapeutic markets with varying degrees of exposure to the price controls in India.

We find a gradual decline in the launch of new molecules in India after the policy, peaking in 2017 with a reduction of 0.8 new molecules launched per firm. This effect was transient and dissipated completely by 2019. The 2019 amendment, which exempted patented drugs from price controls for five years, appears to have been effective in stemming the small decline in drug diffusion to India after the policy. We further show that, beyond India, the policy did not have an economically or statistically significant impact on the launch of new molecules or new clinical trials worldwide.

[20] See Supplementary Section A.2.2 for a complete description of the data.

[21] In Supplementary Figure E11, we describe the dynamics in detailing spending. We find detailing is the highest in the first three to four years after a molecule's launch and then decreases significantly thereafter, with minimal spending in later years. Detailing for regulated products was minimal when the Indian policy took effect, likely because most regulated drugs had been on the market for several years.

5 Evidence on Choice Frictions

As the model highlights, the true welfare benefits of the changes in market outcomes depend crucially on the role of choice frictions. Unfortunately, there are no systematic and comprehensive estimates of the biochemical quality of brands or these choice frictions in the Indian context.[22]

To fill this gap, we measure choice frictions using a sophisticated shopper approach (Bronnenberg et al., 2015; Handel and Kolstad, 2015; Finkelstein et al., 2022). In this approach, we assume that a subset of consumers is not subject to choice frictions, meaning that they choose according to δ^{true} instead of δ. The choices made by these consumers reflect true utility, and the wedge between their choices and those of the average consumer captures choice frictions, conditional on key demographics and preference parameters. In healthcare, physicians are natural candidates for consideration as sophisticated shoppers. They are likely to have the best possible information, and their choices about their own treatment are not driven by agency issues.

In this section, we introduce a novel survey that we conducted to measure physicians' choices and then discuss key descriptive results.

5.1 Physician Survey

Recruitment For our survey, we recruited Indian physicians who were (1) licensed and registered with a legitimate medical board in India and (2) actively practicing. Our focus on licensed physicians is particularly important in India given concerns about the prevalence of poorly trained and informal providers (Das and Hammer, 2014). We obtained physician contacts from a large healthcare marketing company in India that regularly screens its database for unlicensed physicians. We also manually screened out respondents who reported that they are not registered with a medical board or listed a nonexistent state medical board.

We invited 69,702 physicians to participate in our survey by email and text message. The invitation stated that the purpose of the study was to understand physician healthcare choices, that the study had received IRB approval, that their responses would remain anonymous, and that the data would be used exclusively for academic purposes. Physicians were offered Rs. 1,000 ($\approx$ \$14) as compensation for their time upon completing the survey.[23]

[22] Both the relevant academic literature and government inspections have been limited in their coverage. Many practicing physicians and leading public health experts have also expressed concerns about the reliability of government reports, which consistently report a lower prevalence of substandard drugs than academic studies. We summarize the existing academic literature and government reports in Supplementary Section B.

[23] The compensation offered aligns with the upper percentile of the fees charged by physicians practicing

Our final sample consists of 617 physicians. Of the 67,902 invited physicians, 981 started the survey, and 857 were licensed to practice medicine. Among these 857 licensed physicians, 299 physicians had used medications from one of the five therapeutic markets in our structural analysis; they were automatically included in the survey. We randomly selected 318 additional respondents from the remaining physicians to complete the survey for a randomly selected therapeutic market.[24]

Survey Instrument Our survey consists of three main components. The first part asks physicians to report the molecule and brand they used for their own treatment ("baseline choice"). We also ask them to rate the quality and safety of other brands relative to their chosen brand and to qualitatively describe the rationale for their choice.

In the second part of the survey, we ask physicians to make drug choices in two hypothetical scenarios. First, we ask what they would choose if the price of their preferred brand increased by $x\%$, where x is drawn uniformly at random from the set $\{5, 10, 15, 20, 25, 40, 50, 75\}$. Second, we elicit their second choices by asking what brand they would choose if their preferred brand were no longer available.

The third part of the survey measures physician knowledge based on the ranking of their medical school, their type of practice, the number of patients they treat per week, the number of hours they work per week, and their answers to two medical questions often asked in US medical board examinations. [25]

We also ask several additional demographic questions. A copy of the survey instrument is available in the supplementary materials.

5.2 Sample Characteristics

In Supplementary Table F1, we present descriptive statistics of the physicians who completed our survey. The physicians in our sample are 28 years old on average, are primarily general practitioners or primary care physicians (69%), typically work in private healthcare facilities (72%), and work at least a full 40-hour week (68%), and the majority correctly answered the questions from the US medical board examinations (65%).

We benchmark our sample against the samples in two previous studies that conducted physician surveys in India: Das and Hammer (2007) and Das et al. (2022).[26] The first study

in India.

[24] For budgetary reasons, we included only a subset of physicians without any disease.

[25] We selected and validated the medical questions from preparatory materials for US board examinations in consultation with physicians in the US and India.

[26] We cannot directly evaluate the representativeness of our sample as there is no census of medical providers in India.

surveys providers in urban Delhi ($N = 205$), while the second is a representative survey of rural providers in 19 states ($N = 3,473$). Compared to the samples in these other studies, our sample consists entirely of formally trained physicians (100% vs. less than 55%) who are younger (average age 28 years vs. 40–44.12 years), less likely to be male (63% vs. 79%–87.7%), and more likely to have a postgraduate degree (36% vs. 28.5%). More than 65% of the physicians in our sample correctly answered challenging medical questions, while only 30% of the physicians in the other studies could answer basic medical questions.

We deliberately oversample formally trained and highly educated physicians. The goal of our survey is to find physicians whose choices can plausibly serve as a normative benchmark. Therefore, it is desirable for us to select knowledgeable physicians who are *unrepresentative* of the average Indian physician, who is often not formally trained and may be of lower quality, as shown by previous studies (Das et al., 2022).

5.3 Comparison of Patient and Physician Choices

In the left panel of Figure 5, we show that the physicians in our sample are less likely to buy high-priced brands than are consumers. The right panel shows that the physicians rarely choose multinational brands, as consumers often do (Figure 5). Notably, the physicians prefer *specific* Indian manufacturers, such as Cipla and Mankind, across multiple molecules and therapeutic markets. These patterns suggest that the sampled physicians, because of their training and experience, can identify high-quality domestic brands among the cacophony of different options. In contrast, consumers may find it challenging to identify high-quality yet cheap domestic brands and may instead rely on prices and multinational status as coarse signals of quality.

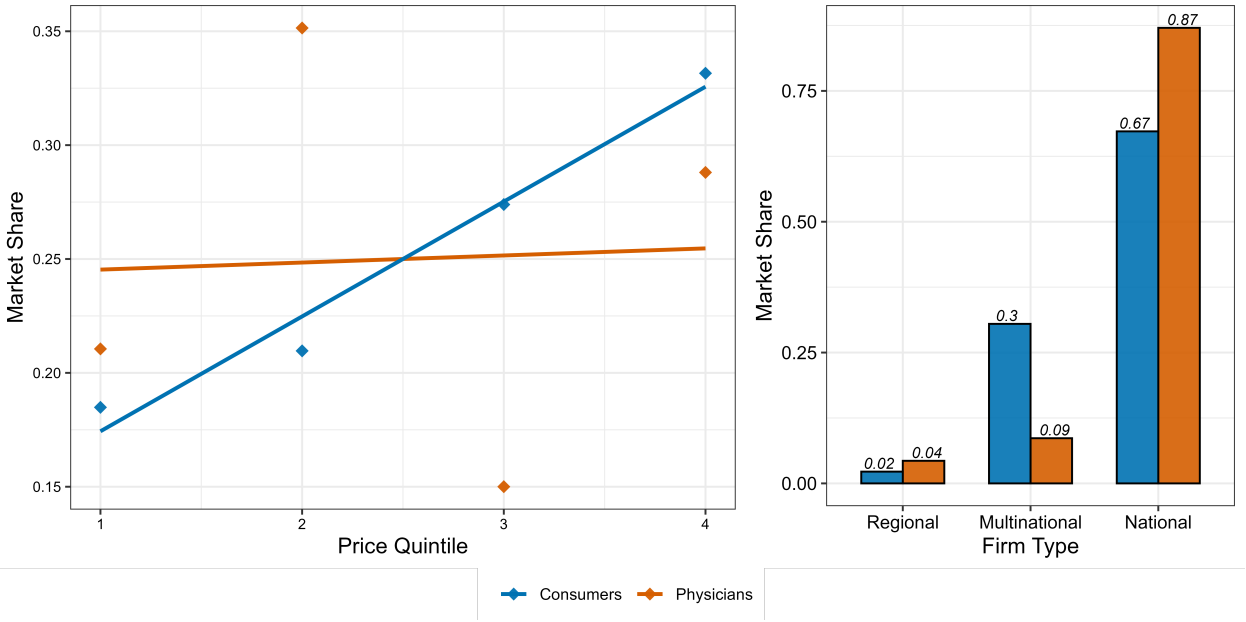
Our qualitative questions provide further insights into factors driving the physicians' choices. The physicians report that they choose their preferred brand because it is easily available in their pharmacy (60%), has a good reputation (50%), and is of high quality (40%) (Supplementary Figure F1). Two out of three of the physicians also report that they typically prescribe specific brands to their patients. Together, these results suggest that the physicians' choices reflect their beliefs about biochemical quality and ease of access, both of which are welfare relevant in our normative framework.

We use various measures of physician knowledge in our survey to further investigate how choices vary with knowledge. In Supplementary Tables F2 and F3, we show that the physician choice patterns remain similar when we restrict the sample to physicians who attended leading medical colleges, those who practice full-time or in leading hospitals, and those who correctly answered both knowledge check questions. As long as these subsamples of the most

knowledgeable physicians are not affected by choice frictions, the choices documented in our survey are similarly free of such frictions.

We emphasize that these descriptive results do not yield estimates of choice frictions δ^{fr} because we have not accounted for differences in other characteristics, such as income, that influence choice. In Section 6.1.4, we formally estimate choice frictions using these data while adjusting for these other factors.

Figure 5: Descriptive Comparison of Physician and Consumer Choices



Notes: The figure presents the within-drug market share on the y-axis for physicians and consumers by different product characteristics. In the left panel, the x-axis shows the price quartile across brands of the same drug, while in the right panel, the x-axis represents the type of firm. Each observation is a brand–drug. The market share of a given brand–drug is the ratio of the sale of that brand–drug to the total sales of that drug. We divide all brands of drugs into quartiles based on price in 2012. The fourth quartile represents the most expensive brand, while the first quartile represents the cheapest brand.

5.4 Taking Stock

We find that the Indian policy substantially lowered the prices of the regulated products. The price declines exceeded the statutory requirement because of the increased price competition induced by the policy. The lower prices in turn increased consumption of previously high-priced brands, which are typically *not* chosen by the physicians in our survey.

We also find an increase in total sales of the regulated drugs. This market expansion reflects both substitutions from other drugs within the same therapeutic class and potentially additional sales from consumers who previously did not buy any drug. Given that the price-controlled drugs were considered essential by regulators, the additional consumption of these

drugs may deliver significant health benefits. Furthermore, this result highlights that certain consumers are willing to buy only specific brands of a drug and would rather buy a different drug than buy a different brand of the same drug.

On the supply side, we find limited evidence of policy-induced product exits on average, although we document some variation across therapeutic classes. We also find no long-run, persistent changes in the launch of new molecules in India.

While these positive results are informative about the potential benefits and costs of the Indian policy, further analysis is needed to precisely quantify the welfare effects and assess alternative policy designs. Importantly, we still need to account for choice frictions and characterize how different market primitives of various therapeutic markets shape heterogeneity in the policy's impacts on market outcomes and social welfare. We aim to address these key questions through the lens of our model.

6 Model Estimation and Results

In this section, we integrate theory and empirical evidence by estimating our model for five important therapeutic categories: ACE inhibitors ("ACE") for hypertension, antacids for acid reflux ("antacids"), blood glucose–lowering drugs for diabetes ("diabetes"), calcium channel blockers ("CCBs") for hypertension, and statins for high cholesterol ("statins"). We focus on these therapeutic markets because they have a high disease burden in India and include many of the drugs regulated by the Indian policy. In Supplementary Section G.1, we outline our selection criteria, discuss specific exclusions, and present descriptive statistics for these therapeutic markets. We estimate our model separately for each therapeutic market. We discuss estimation as if we were analyzing one market, but we will subsequently present the results separately for each market.

6.1 Estimation

Our goal is to estimate the distribution of income and health status $F_s(y_i, \theta_i)$, demand parameters for consumers $\{\alpha_p, \alpha_g, \rho, \delta\}$, marginal costs mc, and choice frictions δ^{fr}. Our estimation proceeds in four steps. First, we estimate the empirical distribution of income and health status using data from a nationally representative health survey. Next, we estimate demand parameters by matching the sales changes associated with the policy-induced price changes through a 2-step generalized method of moments (GMM) estimation procedure (Berry et al., 1995). Third, we obtain marginal cost estimates by inverting the Nash–Bertrand first-order conditions defined in Equation 3.4. Finally, we estimate choice frictions

as the wedge between physicians' and consumers' perceived utility. Note that we do not use information from exit in our estimation because our model does not include fixed costs.

6.1.1 Distribution of Income and Health Status

We estimate the share of consumers with "good" health $Pr_s(\theta_i = g)$ and the distribution of income conditional on health status $\log(y_i|\theta_i) \sim \mathcal{N}(\mu_{\theta_i s}, v^2_{\theta_i s})$ by matching the empirical distribution observed in LASI.[27] This nationally representative health survey, conducted between April 2017 and December 2018, includes microdata on the diseases that each individual has or had in the past year, her income,[28] and her self-reported health status.

6.1.2 Demand Parameters

Next, we estimate the demand parameters $\theta^d = \{\alpha_p, \alpha_g, \rho\}$. Recall that α_p and α_g capture the price sensitivity of consumers with poor and good health, respectively, and ρ captures the relative importance of molecule-level shocks. We estimate these parameters using the GMM estimation procedure from Berry et al. (1995). The estimand is

$$\theta^d = \arg\min_{\theta} \mathbf{E}(\Delta\xi_{jst} Z_{jst}|X_{jst}) W \mathbf{E}(\Delta\xi_{jst} Z_{jst}|X_{jst}) \,,$$

where $\Delta\xi_{jst} = \xi_{jst} - \xi_{jst=2013}$ is the difference in unobserved demand shocks for year t relative to when the Indian policy was implemented, Z_{jst} is instruments, X_{jst} is controls, and W is the optimal weighting matrix from the two-step GMM. For a given value of θ^d, $\delta_{js} + \xi_{jst}$ is determined by the standard contraction mapping that equates the model-implied market shares with the observed market shares. We then take fixed differences to evaluate $\Delta\xi_{jst}(\theta^d)$. Our estimator minimizes the sample analog of this objective function.

The key threat to identification is that changes in sales and prices after the policy may be confounded by unobserved demand shocks. To address this challenge, we use the statutory price changes implied by the Indian policy to construct instruments Z_{jst}, which we argue are independent of unobserved demand shocks and provide the variation necessary to identify the parameters of interest.

To construct our instruments, we simulate the statutory price changes mandated by the Indian policy. As demonstrated in the event study analysis, the policy generated rich variation in price changes based on the pre-policy price levels of the regulated products. Our instruments isolate these policy-induced price changes, allowing us to identify θ^d from the

[27] See Supplementary Section A.2.3 for details on LASI and variable definitions.

[28] We measure income using daily consumer expenditure because of the challenges associated with directly measuring income in LMICs (Poirier, 2024).

post-policy sales responses to these price changes.

Formally, let $T_{js} = 1\{js \text{ is price controlled}\}$ indicate whether drug j in state s is regulated. Recall that the price ceiling for a regulated product is the mean price of all products of the same molecule $\overline{p_m}$, which we simulate using the pre-policy prices ($t = 2011$).[29] The simulated price change for a product is $E_{js} = \max(p_{js} - \overline{p_m}, 0)$.

We construct three instruments for a product j based on simulated price changes of the focal product and its rivals. Our first instrument is a product's own price change: $Z_{1jst} = 1\{t > 2013\} \times T_{js} \times E_{js}$. The second instrument, Z_{2jst}, is the simulated average price change of other products of the same molecule. We interact this instrument with discrete bins of pre-policy price levels G_{js} to capture heterogeneity in responses to rivals' price changes, where $G_{js} = h$ if $p_j > 1.1\overline{p_m}$, $G_{js} = l$ if $p_j < 0.9\overline{p_m}$, and $G_{js} = m$ otherwise. The third instrument, Z_{3jst}, is the simulated average price changes of *other* molecules in the same therapeutic market.[30]

In Supplementary Section G.2, we use an example to illustrate how different moments map to different parameters of interest and show that our instruments provide sufficient variation for identification. Briefly and heuristically, the correlation between a product's price change Z_{1jst} and its own sales change identifies aggregate price sensitivity. The heterogeneous sales responses to rivals' price changes by pre-policy price levels Z_{2jst} identifies the heterogeneity in price sensitivity. Greater dispersion in price sensitivity implies that price reductions for once-high-priced products will disproportionally divert sales from other, similarly high-priced products. Finally, the correlation between a product's sales changes and the price changes of other molecules Z_{3jst} identifies ρ, which governs cross-molecule substitutions.

The key identification assumption is that changes in unobserved demand shocks after the policy are independent of the simulated price reductions, conditional on the specified controls $\mathbf{E}\left(\Delta\xi_{jst}|Z_{jst}, \gamma_{st}, \gamma_{G_{js}T_{js}t}\right) = 0$ (Berry and Haile, 2014).[31] We include regulation status T_j–price level G_j–year fixed effects $\gamma_{G_jT_jt}$ as controls. These controls help account for time-varying confounders that affect all regulated products, such as increased consumer awareness after the Indian policy announcement. Thus, we use the granular variation in the *magnitude* of the policy-induced price changes for identification, rather than the changes induced by regulation status. We also include state–year fixed effects γ_{st} to control for

[29] Strictly speaking, the price ceiling was set at the molecule–dose level. However, in the vast majority of cases, all doses of a molecule were regulated.

[30] Formally, $Z_{2jst} = 1\{t > 2013\} \times G_{js} \times \sum_{j' \neq j} 1\{m(j') = m(j)\} E_{j's} s_{j's}$ and $Z_{3jst} = 1\{t > 2013\} \times \sum_{j' \neq j} 1\{m(j') \neq m(j)\} E_{j's} s_{j's}$.

[31] We test the relevance assumption in Supplementary Tables G2 and G3. We find that F-statistics of a regression of the instruments on price changes exceed 100 in all cases, alleviating concerns about weak instruments.

macroeconomic trends in different states.

Our event study analysis and additional placebo tests validate the exclusion restriction. We find no pretrends in prices before the implementation of the Indian policy and no evidence of anticipation effects. In Supplementary Figure G2, we examine the correlation between the statutory price reductions E_{js} and year-over-year price changes for $t \in \{2012, 2016, 2019\}$. Our results are inconsistent with serial correlation in unobservables: E_{js} is strongly correlated with price changes during the policy rollout ($t = 2016$) but not before the policy ($t = 2012$) or after its full implementation ($t = 2019$). Furthermore, a post-estimation check shows little correlation between the simulated price changes and changes in the empirical analogs of unobserved shocks (Supplementary Figure G3). Together, these findings support the assumption that changes in unobserved demand shocks are independent of our instruments.

Perceived Product Quality Given estimates of $\{\alpha_p, \alpha_g, \rho\}$, we estimate $\delta_{js} + \xi_{jst}$ by matching observed market shares using the standard BLP contraction mapping procedure (Berry et al., 1995). We estimate the time-invariant perceived product quality $\hat{\delta}_{js}$ as the mean over time $\frac{1}{T}\sum_{t=2011}^{2014} \delta_{js} + \xi_{jst}$.

6.1.3 Marginal Costs

Our estimate of mc_{jst} is the value that rationalizes the observed prices under our Nash–Bertrand pricing assumption for each period t. We estimate marginal costs only for $t < 2014$, as the standard Nash–Bertrand assumption no longer holds once the price ceilings are in place (Dubois and Lasio, 2018) and because we use only pre-policy costs in our policy analysis.

6.1.4 Choice Frictions

In Section 5.3, we documented systematic differences between the choices of consumers and physicians. We build on this descriptive pattern to formally estimate choice frictions.

We maintain two key assumptions. First, we assume that

Assumption 6.1. *Physicians are informed about true product utility* $\delta_j^{phy} = \delta_j^{true}$.

As discussed earlier, the licensed and high-quality physicians in our survey have the best possible knowledge about healthcare products because of their medical education, training, daily practice experiences, and access to a peer network of knowledgeable colleagues. In addition, by asking physicians to report choices for their *own* treatment, we limit the agency frictions that could distort their brand choices for patients. The choice patterns in the survey are robust to our restricting the sample to the most knowledge physicians, further validating that these choices are free of frictions and reflect true product quality.

The differences in brand choices made by consumers and physicians could reflect not only choice frictions but also other factors such as differences in income and price sensitivity. Therefore, we cannot directly estimate choice frictions using observed market shares. To isolate choice frictions, we must first use our model to recover physicians' perceived utility δ^{phy} conditional on these other factors.

We estimate the primitives for physician preferences, $\{\alpha^{\text{phy}}, \rho^{\text{phy}}, \delta^{\text{phy}}\}$, by maximizing the likelihood of the choices recorded in our survey. Recall that we asked physicians to report three choices: the choice for their own treatment ("baseline choice"), the choice with a random price increase for the baseline product, and the choice when the baseline product is removed from the choice set ("second choices"). We specify physician preferences using the same utility function in Equation 3.1, which determines the model-implied probabilities of these choices as a function of $\{\alpha^{\text{phy}}, \rho^{\text{phy}}, \delta^{\text{phy}}\}$. Given the observed choices and model-implied conditional choice probabilities, we use maximum likelihood estimation to recover $\{\alpha^{\text{phy}}, \rho^{\text{phy}}, \delta^{\text{phy}}\}$. See Supplementary Section G.3 for a detailed discussion of the likelihood construction and the estimation procedure.

With these estimates in hand, we recover choice frictions as the difference in the perceived product utility between patients and physicians $\delta^{\text{fr}} = \delta - \delta^{\text{phy}}$. Our estimation is valid under the following assumption:

Assumption 6.2. *Conditional on income, price sensitivity, and willingness to substitute across molecules, physicians and patients have the same choice probability for a brand* $\sigma^{phy}_{ij|m}(p, \delta | y_i, \alpha_i, \rho) = \sigma_{ij|m}(p, \delta | y_i, \alpha_i, \rho)$.

Under this assumption, consumers would choose according to δ^{phy} instead of δ in the absence of choice frictions, leading to a change in choice probabilities $\Delta\sigma_{ij|m} = \sigma_{ij|m}(p, \delta^{\text{phy}} | y_i, \alpha, \rho) - \sigma_{ij|m}(p, \delta | y_i, \alpha, \rho)$. (Going forward, we refer to this difference in choice probabilities as the "choice wedge.") Note that while the choices of consumers and physicians can still differ because of differences in y_i, α, ρ, the choice probabilities are the same when these primitives are fixed and there are no choice frictions.

This assumption may be violated if some welfare-relevant factors other than income, α and ρ also influence brand choices and differ systematically between physicians and consumers. To investigate this potential concern, we implement an additional consumer survey that elicits the drug choices of different consumer groups, such as lawyers, government employees, and school teachers (Supplementary Section F.1.1). We find that consumers' brand choices do not systematically vary with sex, employment status, or industry, conditional on location and income (Supplementary Table F8). However, consumers who are more educated and correctly define a generic drug are less likely to buy expensive brands. In addition, we

also surveyed 60 pharmacists. We also find that pharmacists, especially those who have worked for more than a year and received formal pharmacy degree, are less likely to buy expensive brands (Supplementary Table F9). Together, these patterns suggest that differences in choices reflect differences in information, and not differences in preferences.

6.2 Results

Consumer and Physician Preferences In the top part of Table 1, we report our estimates of consumer preference parameters $\{\alpha_p, \alpha_g, \rho\}$. Our estimates imply that consumers in poor health are less price sensitive than those in good health, although these differences are small in many therapeutic markets. Consumers are most price sensitive for antacids, which, in contrast to the other therapeutic markets we study, are used to relieve symptoms for a non-life-threatening condition. Consumers substitute across molecules more frequently in the statins market ($\rho = 0.19$) and less so in the ACE, antacids, and CCB markets($\rho > 0.50$).

In most cases, we find that the physicians are less price sensitive than consumers and less willing to substitute across molecules. Low price sensitivity implies that the physicians' choices for their own treatment are largely driven by their beliefs about product quality δ^{phy}. Low price sensitivity is consistent with the qualitative patterns we documented earlier: The physicians rarely report that low prices are a factor in their choices (Supplementary Figure F1).

Own-Price Elasticity & Markups We find that sales-weighted average own-price elasticities range from -1.59 to -2.49. Additionally, our estimates imply that prices are 2.05 to 11.91 times marginal costs, indicating substantial markups in all markets. Markups are the highest in the diabetes and CCB markets and lowest in the ACE market. We also find significant variation in markups across different brands of the same molecule, highlighting that some brands command more market power than others.

Our marginal cost estimates align with the accounting estimates of production costs found in Hill et al. (2018). Our estimates of elasticities and markups are similar to the findings from other studies in pharmaceutical markets (Dubois and Lasio, 2018), although we find higher markups for diabetes drugs.

Choice Frictions We find that consumers overvalue expensive multinational brands because of choice frictions. In Figure 6, we show the aggregate change in market shares for brands in different pre-policy price quartiles if consumers were to choose according to δ^{true} instead of δ. The figure shows that consumers overconsume expensive brands, especially in the ACE market. These patterns are particularly important for the welfare effects of the

Table 1: Estimated Parameters and Summary Statistics of Model Primitives

	ACE	Antacids	CCBs	Diabetes	Statins
Consumer Preference Params.					
α_g	34	80.03	20.06	23.38	20.88
	(0.014)	(0.001)	(0.004)	(0.002)	(0.001)
α_p	13.74	20.01	60.08	23.31	19.95
	(0.042)	(0.001)	(0.003)	(0.001)	(0.001)
ρ	0.57	0.53	0.5	0.28	0.19
	(0.026)	(0.001)	(0.002)	(0.001)	(0.001)
Physician Preference Params.					
α^{phy}	11.04	5.39	26.48	7.86	7.06
	(1.306)	(0.194)	(3.043)	(0.185)	(0.953)
ρ^{phy}	0.86	0.6	0.85	0.24	0.88
	(0.017)	(0.016)	(0.018)	(0.027)	(0.017)
Summary of Model Primitives					
Avg. Price Elasticity	-2.49	-2.24	-1.59	-1.60	-1.84
Avg Markup p/mc	2.02	1.91	12.04	11.51	5.87
Coef. of Var. p/mc	0.19	0.19	0.74	0.99	0.97
$cor(mc, \delta^{\text{true}})$	0.44	0.34	0.12	0.24	0.61
Coef. of Var. δ	2.78	1.68	0.51	0.45	0.64
Coef. of Var. δ^{true}	1.76	1.43	0.45	0.54	0.58

Notes: The table presents the demand parameters and summary statistics of model primitives. The top and middle panels present the estimate parameters with standard errors in parentheses. The bottom part of the panel presents the means of the different primitives across drugs. Coefficient of variation is the standard deviation divided by the absolute value of the mean.

Indian policy, which induced the largest price reductions for these expensive brands (Supplementary Figure G7). Consumers systematically overconsume multinational brands such as Sanofi and AstraZeneca because of choice frictions (see Supplementary Figure G5 and Supplementary Table F6 for the companies with the most and least bias).

Variation in Product Utility We find substantial variation in true utility between different brands of the same drug, likely reflecting the lack of rigorous quality standards in India. This contrasts with the situation in high-income countries, where there is little difference in true utility between different brands (Bronnenberg et al., 2015). We also find that the variation in true utility is generally smaller than the variation in perceived utility in most therapeutic markets. This suggests that choice frictions have led to artificial product differentiation and exacerbated market power.

Correlation Between Costs and True Quality We find a positive correlation between marginal costs and true quality across all five therapeutic markets. This suggests that strin-

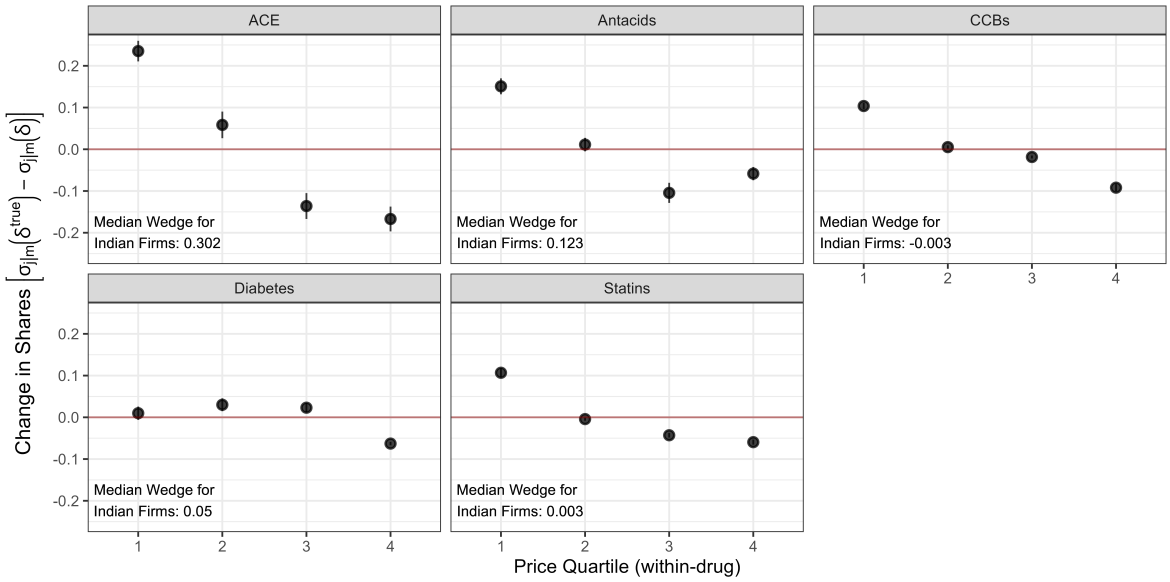
gent price controls that lead to product exits likely would have negative welfare consequences.

Robustness and Validation Our demand estimates are robust to model misspecification in two key ways. Under the exclusion restriction, our estimates capture the causal relationship between prices and sales even if our demand model is misspecified (Andrews et al., 2024). Second, since our identification strategy leverages policy-induced price variation rather than supply-side moment conditions, our estimates of consumer preferences are robust to misspecification of our supply model and any dependence between demand and supply shocks.

In Supplementary Table G4, we evaluate our model's performance in predicting out-of-sample exits. (Recall that we do not use exit for estimation.) We find that the accuracy of the model, defined as the share of the model-predicted exits that match observed exits, ranges from 87% to 96% across different therapeutic markets. For products with a pre-policy market share greater than 5%, the accuracy is even higher, at 93%–99%. Given that there were relatively few exits in the data, the prediction errors likely reflect false exits. The exit patterns predicted by the model are also consistent with the corresponding event study estimates for these markets (Supplementary Figure E28).

In Supplementary Section G5, we report the sensitivity of the parameters to the moment conditions (Andrews et al., 2017). This allows readers to assess how our estimates would change locally under potential violations of individual moment conditions.

Figure 6: Price Differences and Choice Wedges



Notes: The figure presents the relationship between the relative price of brands on the x-axis and the aggregate choice wedge $\int \sigma_{ij|m}(\delta^{\text{true}}|y_i, \alpha, \rho) - \int \sigma_{ij|m}(\delta|y_i, \alpha, \rho)$—the change that would occur if consumers chose according to δ^{phy} instead of δ—on the y-axis. Brands are divided into deciles based on prices from the AIOCD. Each point represents the mean choice wedge for a given decile. The median change for Indian manufacturers is noted in the bottom-left corner.

7 Policy Analysis

With the parameters of our model estimated, we are ready to quantify the welfare effects of the Indian policy and evaluate alternative policies. Differences across therapeutic markets provide valuable variation to assess policy performance under different market conditions.

In each counterfactual scenario, we compute an equilibrium by iterating over firms' best responses until convergence.[32] We then calculate profits, consumer surplus, and total welfare at this equilibrium, with and without adjustment for choice frictions in calculating consumer surplus. We report the changes in these outcomes relative to the pre-policy market equilibrium outcomes in 2013, aggregating across all states.

The unit, unless otherwise specified, is dollars per person per year, assuming that a consumer takes one standard dose (i.e., one DDD) each day over the course of a year. We use this per-capita measure to simplify exposition. The market size ranges from 5 million to 30 million people, implying that the aggregate welfare effects are substantial.

[32]See Supplementary Section G.4 for details on our computational algorithm and our tests for multiple equilibria.

7.1 Welfare Effects of the Indian Policy

Figure 7 summarizes the effects of the Indian policy on drug prices, consumption, and welfare. On average, we find that prices decrease by between 18% and 29%, consistent with our event study estimates in Section 4. The price reductions are larger in therapeutic markets with larger pre-policy price dispersion, such as the statins market.

The price ceilings increase consumption without inducing many exits. The increase in consumption is particularly high in the ACE and statins markets, where the price reductions are larger and consumers are more price sensitive. Importantly, the policy leads to a 0.03–0.11 p.p. increase in consumption of the essential drugs regulated by the policy.[33] Thus, the Indian policy accomplished the goal of improving drug access. Although the policy reduces firms' profits by \$0.87 to \$5.14 per capita, firms find it profitable to remain in the market, and exits are infrequent.

Under reveled preference, consumer surplus increases by between \$0.92 and \$5.06. The increase in consumer surplus occurs through two channels. First, price-insensitive consumers who previously bought expensive brands now pay less because of the lower prices. In our model, these tend to be higher-income, sicker consumers (Supplementary Figure G6). This change represents a transfer from firms to consumers. Second, lower prices result in substitution toward the now-cheaper brands, generating efficiency gains.

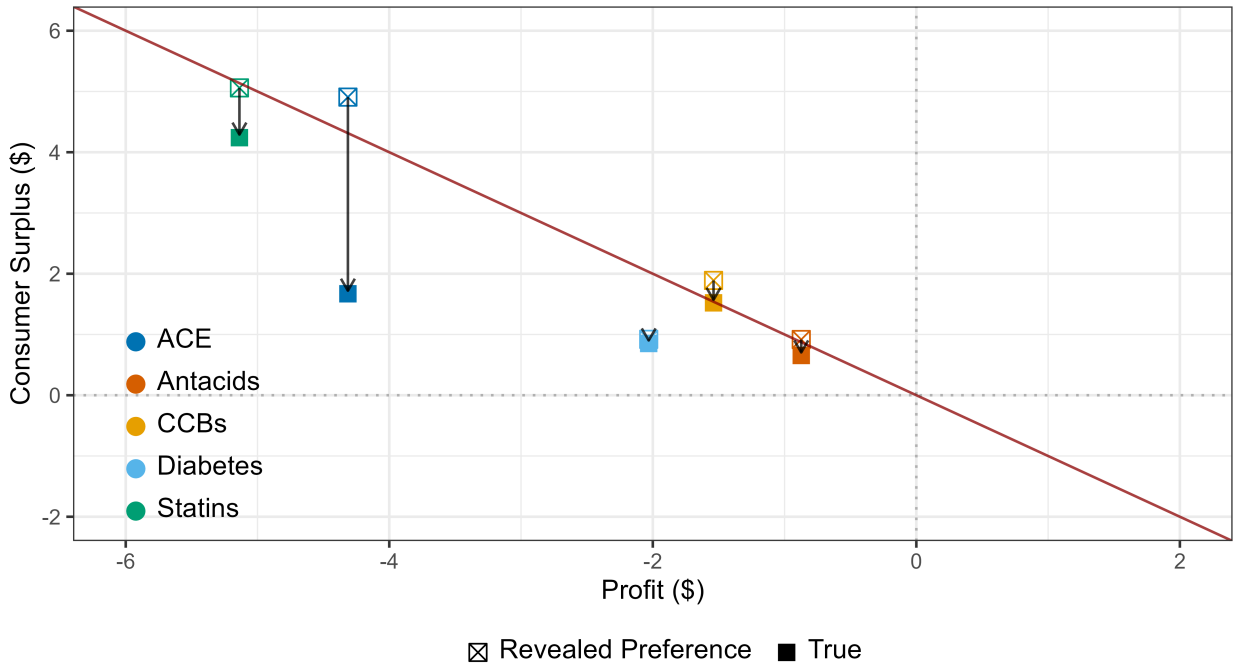
The changes in total social welfare range from −\$1.11 to \$0.59. This net effect reflects two countervailing forces: welfare gains from correcting market power and welfare losses due to product exits. The former dominate in most therapeutic markets, while the exit of a product with particularly high perceived utility resulted in a net welfare loss in the diabetes market.

The increase in consumer surplus is 30% to 50% smaller once we account for choice frictions, as the Indian policy disproportionately steered consumers toward overvalued products. For illustration, we return to the example of Ramipril. Cardace was the most expensive and highly valued Ramipril brand prior to the policy. The policy lowered Cardace's prices by 40%, attracting some consumers who had previously bought Ziram. Cardace and Ziram have similar true utility, and Ziram's pre-policy price was *lower* than Cardace's post-policy price. Thus, marginal consumers who switched ended up paying more for a similar-utility product, leading to a welfare loss.

The true gains in consumer surplus range from \$0.65 to \$4.24 after choice frictions are

[33] Although our welfare measures partly capture the benefits from this increased consumption, our calculations may understate the true benefits for two reasons. First, consumers may underestimate the true benefits of preventive treatments, such as statins. Second, we do not measure or account for public health externalities. We plan to formally account for these features in future work.

Figure 7: Welfare Impacts of the Indian Policy Under Different Normative Benchmarks



	ACE	Antacids	CCBs	Diabetes	Statins
Positive Outcomes					
Prices (%)	-0.23	-0.20	-0.18	-0.22	-0.29
Share Regulated (p.p.)	0.11	0.03	0.04	0.03	0.09
Share Inside (p.p.)	0.04	0.02	0.03	0.02	0.05
Share Exit (%)	0.06	0.06	0.02	0.04	0.06
Normative Outcomes					
Profit ($)	-4.31	-0.87	-1.54	-2.03	-5.14
Revealed C.S. ($)	4.91	0.92	1.89	0.92	5.06
Revealed Welfare ($)	0.59	0.04	0.35	-1.11	-0.08
True C.S. ($)	1.67	0.65	1.52	0.85	4.24
True Welfare ($)	-2.64	-0.22	-0.02	-1.18	-0.90

Notes: The figure presents the change in profits on the x-axis and change in true consumer surplus on the y-axis. Each point is a therapeutic market differentiated by color. The different shapes denote different normative benchmarks. A policy on the 45-degree line implies no change in net welfare, while a policy change to the top-right of the 45-degree line implies an increase in welfare. The perpendicular distance between the 45-degree line and a point measures the magnitude of the change. The table presents the change in key positive and normative outcomes. Each column denotes a therapeutic market, and each row is an outcome. The outcomes measure the change relative to the outcomes in the no-policy equilibrium in $ per capita per year. We present the median change in outcomes across all states in 2013. The outcomes are formally defined in Section 3

accounted for. To put these changes into perspective, a year's supply of statins cost $54.9 in 2013, utilizing 9% of the median household's consumption budget. The Indian policy improved consumer surplus in this market by $4.24, which is equivalent to a savings of 7.9% of statin costs or 1% of the median household expenditure. Across the therapeutic markets, the increase in consumer surpluses ranges from 2% to 9% of treatment costs for a year. Naturally, the gains are more substantial for sicker patients who need multiple doses and suffer from multiple diseases.

After firm profits are accounted for, total social welfare decreases by $2.64, $1.18, $0.90, and $0.22 in the ACE, diabetes, statin, and antacid markets, respectively. Social welfare remains unchanged in the CCB market, where choice frictions are smaller.

These results highlight an important interaction between market power and choice frictions. In the absence of choice frictions, price ceilings correct monopoly distortions and improve social welfare. However, when both market failures are present, high prices due to markups steer consumers away from overvalued products, similarly to a corrective tax. The Indian price controls reduce one market failure by reducing markups but inadvertently exacerbate the harms from the other market failure.

The Indian policy had two key shortcomings. First, the policy was poorly targeted in that it induced the largest price changes for products that are typically overvalued, exacerbating the negative effects of choice frictions. Second, the policy imposed the same price ceiling for all products. Although exit was not a major issue with the Indian policy, any further lowering of price ceilings risks triggering exits of high-quality products, which tend to have higher marginal costs.

7.2 Choosing Price Ceilings

Price controls are not a binary policy: importantly, regulators must choose the price ceiling level. We explore how regulators can effectively set price ceilings. Consistent with the Indian policy, we evaluate price caps at the drug level, ranging from the lowest to the highest pre-policy brand prices. The results are presented in Figure 8.

If a regulator imposes a very low price ceiling, prices fall substantially, but many high-utility brands exit. The harms from exit then dominate the loss from lower prices, lowering consumer surplus in most markets. Interestingly, the loss in true surplus is smaller than the loss in revealed-preference consumer surplus because some of the products that exit were overvalued. Higher price ceilings, close to the pre-policy price of the median brand, strike a balance between reducing markups and preventing exit. For such price ceilings, consumers perceive a gain in consumer surplus.

The optimal price ceiling to maximize consumer surplus differs among therapeutic markets based on prepolicy markups. In the CCB and diabetes markets, where markups are high, price ceilings as low as 20$^{\text{th}}$ percentile of the prepolicy price distributions do not lead to exit and benefit consumers. In contrast, in the ACE, statin, and anatacid markets, where markups are relatively small, such low price ceilings are harmful and the optimal price ceiling is much higher. Thus, even for the same industry in the same country, optimal regulation depends on the nature of competition.

We find, as we did for the Indian policy, that the true gain in consumer surplus is smaller than that perceived by consumers and true social welfare decreases. Because consumers overvalue expensive brands, a price ceiling will mechanically have the largest impact on these brands, leading to overconsumption of overvalued products. In fact, *any* drug-level price ceilings will disproportionately impact expensive overvalued brands, making it difficult to improve allocative efficiency. If there were no choice frictions, regulators could improve efficiency by reducing markups and allowing consumers to switch to products that they value. In all markets, we can find welfare-improving price ceilings under revealed preference. However, consumers will typically switch to overvalued products, limiting the welfare benefits of the policy. Although consumers can be made better off because of transfers, such switching is not efficient. Even in the best case, drug-level price ceilings are inefficient.

A potential solution is to set granular price ceilings at the brand level using information about costs, quality, and markups. Such policies would be similar in spirit to the cost-based price caps implemented in India on a much smaller scale in 1995.[34] Of course, the efficacy of these caps depends on whether regulators have accurate and detailed information. Regulators need not be perfectly informed—effective policies can be designed with only coarse information on economic primitives. For example, if regulators know an upper bound on costs and which products are overvalued (e.g., multinational brands), a price ceiling at the cost bound for weakly undervalued brands robustly improves welfare, as we argue theoretically (Supplementary Section G.5) and illustrate empirically (Supplementary Figure G14).[35] Another solution is to reduce choice frictions with nonprice interventions.

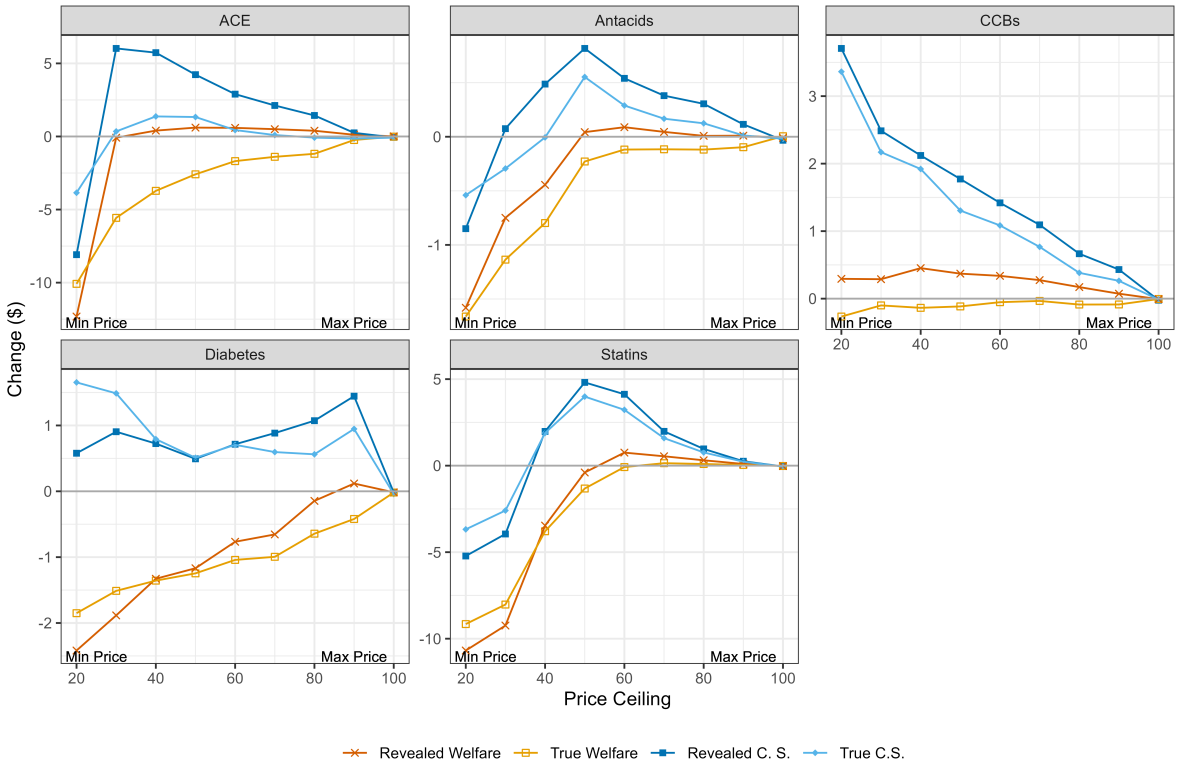
7.3 Reducing Choice Frictions

Instead of regulating market prices, policymakers can attempt to reduce choice frictions. Insofar as correcting choice frictions reduces product differentiation, such a policy would also reduce market power. We evaluate an idealistic case where all choice frictions are eliminated,

[34] In 1995, prices ceilings were set to a fixed markup of distribution costs, outward freight, manufacturer margin, promotional expenses and trade commissions, as determined by the Indian regulators.

[35] Formally, such a policy is the optimal under a minmax loss function.

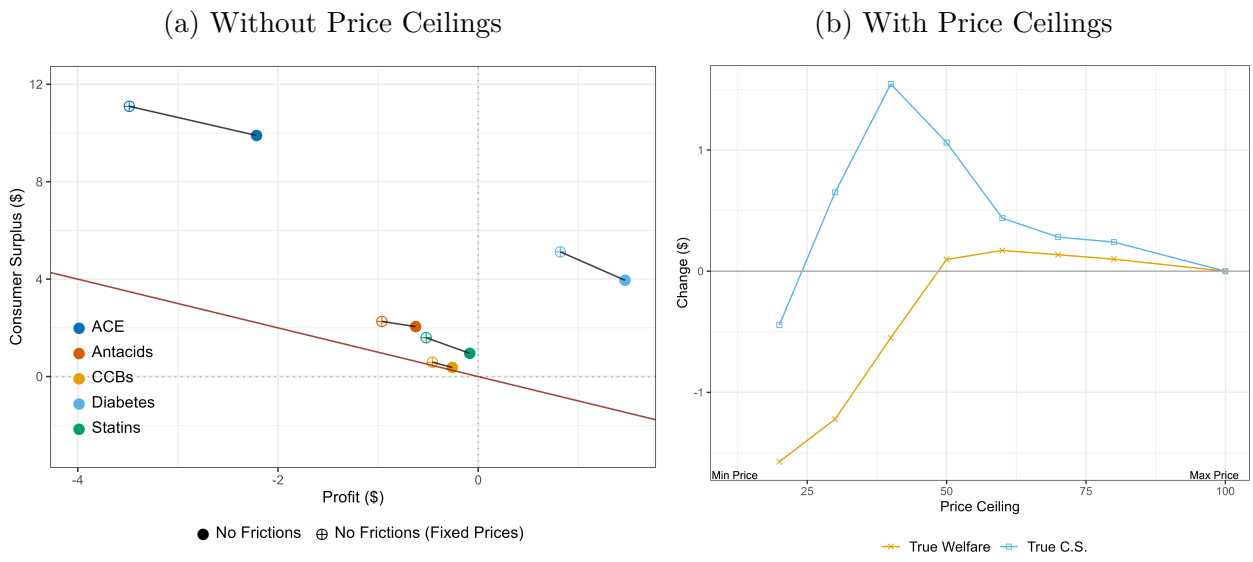
Figure 8: Welfare Effects at Different Price Ceilings



Notes: The figure presents the change in profits, consumer surplus, and net welfare, separated by different colors and shapes, on the y-axis and different price ceilings on x-axis. For a given point on the x-axis (e.g., 50), the price ceiling is the corresponding percentile (e.g., median) of the pre-policy price distribution across brands. The different panels represent different therapeutic markets. The outcomes measure the change relative to the outcomes under the no-policy equilibrium in $ per capita per year. The change in welfare from the Indian policy is annotated on the figure. We present the median change in outcomes across all states in 2013. The outcomes are formally defined in Section 3.

allowing consumers to act according to the true utility δ^{true}. The results are presented in Figure 9. In practice, eliminating choice frictions is challenging for at least two reasons. First, we need to understand the mechanism driving the choice frictions to design specific interventions. Policies to increase consumer awareness are central if information is the key issue, while agency frictions call for policies that curtail distortionary financial incentives for physicians. Second, designing effective policies for a specific mechanism is challenging, as evidenced by the limited benefits of information interventions (Carrera and Villas-Boas, 2023). These important questions are beyond the scope of this paper but warrant thoughtful consideration in future work.

Figure 9: Impacts of Eliminating Choice Frictions



Notes: In the left panel, the figure presents the change in profits on the x-axis and change in true consumer surplus on the y-axis, with therapeutic markets differentiated by color. The right panel presents the impacts, aggregated across all therapeutic markets, of different price ceilings once choice frictions have been corrected. The outcomes measure the change relative to the outcomes under the no-policy equilibrium in $ per capita per year. We present the median change in outcomes across all states in 2013. The outcomes are formally defined in Section 3. The right panel presents the mean choice friction on the x-axis and the median change in net welfare on y-axis.

In our first counterfactual, consumers act according to δ^{true}, while prices remain unchanged. Unsurprisingly, this intervention improves consumer surplus, as some consumers switch from expensive overvalued brands to cheaper undervalued ones. In markets where the choice frictions were large, the increase in consumer surplus is substantial: $11.09 in ACE and $5.11 in diabetes (Supplementary Table G9). The intervention also redistributes profits from overvalued to undervalued firms and slightly reduces total profits.

Next, we allow firms to reoptimize prices after the choice frictions are removed. We find that average markups do not change significantly, as there continues to be significant variation in true quality across brands (Supplementary Table G6). Previously undervalued local

manufacturers increase prices and capture some consumer surplus (Supplementary Figure G8). The impact on total social welfare remains similar to the case where prices remain unchanged (Supplementary Table G10).

A limitation of only removing choice frictions is that it does not address market power that arises from true quality differences. In Supplementary Figure G9, we show that even after all choice frictions are eliminated, more than 55% of the first-best surplus remains.[36] An exception is the ACE market, where eliminating choice frictions achieves 80% of the first-best welfare gains.

Addressing both market failures is important. In Figure 9b, we present the welfare impacts of different price ceilings after the choice frictions have been removed. For a wide range of price ceilings, we find that price controls improve both consumer and social welfare on aggregate and for each therapeutic market (Supplementary Figure G10).

7.4 A Broader Set of Policies

We briefly discuss three additional policies commonly implemented in other countries to address similar issues: government entry, generic substitution, and quality standards. Since India has not implemented such policies, we must make important assumptions about their implementation and certain economic primitives (e.g., the fixed cost of introducing a public option). Based on these assumptions, we use our model to predict the impact of these policies. Given the tentative character of these assumptions and the model-based extrapolation, these results should be viewed as exploratory evidence on key questions that warrant more rigorous analysis in future research.

Government Entry Under this policy, the regulator launches a high-quality government brand sold at marginal cost, which consumers undervalue to a similar extent that they do the average Indian-manufactured brand. Price-sensitive consumers switch to this low-cost, high-quality public option despite choice frictions. In addition, private prices decrease because of the increased competition, benefiting all consumers. In aggregate, the policy improves consumer surplus and overall welfare, before the fixed cost of launching the public option is taken into account. (See Supplementary Section G.6 for details.)

Generic Substitution A generic substitution policy requires consumers to purchase the cheapest brand of each drug, forcing all firms selling the same drug to engage in *undifferentiated* Bertrand competition. In equilibrium, the product with the lowest marginal cost

[36] In Supplementary Table G16, we report the same measure for all policies.

remains in the market and charges the second-lowest marginal cost. In our setting, since marginal costs are positively correlated with true quality, the remaining products tend to be of lower quality. The gains from low prices are outweighed by the loss from high-quality brands exiting the market. Consequently, consumer surplus, profits, and overall welfare decline. (See Supplementary Section G.8 for details.)

Quality Standard When a minimum quality standard is enforced, substandard brands either exit the market or invest in upgrading their quality. In the former case, the market consists of only a few expensive, high-quality brands, and the loss of access to low-cost options reduces consumer surplus and total welfare. If substandard brands can improve quality at minimal costs, the market will contain more medium- to high-quality products. In this scenario, consumer surplus, profits, and overall welfare all increase, although drug prices would be higher. (See Supplementary Section G.7 for details.)

8 Conclusion

In this paper, we study the welfare effects of a pharmaceutical price control policy in India. We document three key empirical facts: First, the Indian policy resulted in a large decrease in the prices of expensive branded drugs, leading consumers to purchase more of these branded drugs. Second, despite the large price reductions, there was limited disruption of supply. Finally, choice frictions lead consumers to choose expensive brands over cheaper brands of similar quality.

We combine these empirical patterns with our model to assess the Indian policy and alternative policies. Under revealed preference, lower prices increase consumer surplus by (1) transferring surplus from firms to inframarginal consumers and (2) improving allocative efficiency among marginal consumers. However, the true benefits are smaller, as consumers overestimate the benefits of the expensive brands. Indeed, total welfare declines. Welfare-improving policies, such as cost-based caps and choice friction reductions with price caps, instead address the two market failures—market power and choice frictions—simultaneously.

More generally, we show that effective price regulation must consider market power, choice frictions, and their interaction. In an attempt to correct distortions due to market power, the Indian policy inadvertently exacerbated the negative impacts of choice frictions, ultimately lowering welfare. In addition, there is considerable variation in how these forces play out in different therapeutic markets, even within a country. Therefore, it is important to quantify the key economic primitives by combining theory and data. Our analysis, although tailored to the Indian setting, provides a framework for future research on price controls in

other contexts. For example, the pricing and utilization of antibiotics may be influenced by similar forces. Outside healthcare, the effect of tax credits for electric vehicles can depend on consumer understanding of their pros and cons and manufacturers' ability to capture the tax credits.

Several key questions related to price controls, especially in pharmaceutical markets, remain for future research. First, the distributional consequences of price controls are not yet well understood, despite the importance of health equity as a policy objective. Second, understanding the effects of price controls on how consumers learn about new brands and molecules is vital for a more comprehensive evaluation. Third, pharmaceutical markets are increasingly "global," with policies in one country impacting supply in others. The trade-offs of price regulation in a global context, taking into account complementary and competing interests across countries, is an important space for future research.

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