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

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Abstract

We study how two common market failures—market power and choice frictions—shape the welfare effects of a large-scale pharmaceutical price control policy in India. The policy reduced the prices of regulated drugs by 24% and increased their sales by 36%, with minimal impact on product entry or exit. A standard revealed-preference welfare analysis suggests substantial gains in consumer and social surplus, as price caps correct monopoly distortions. However, using a survey of physicians' own drug choices validated with laboratory drug tests, we show that consumers systematically overvalue regulated products. Incorporating these choice frictions reduces estimated consumer surplus gains by 30% and reveals an overall decline in social welfare. We also evaluate alternative price and nonprice regulations that address both market failures.

Keywords: Price controls, imperfect competition, product quality, pharmaceuticals
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1 Introduction

High and rising drug prices are a central policy issue, especially in low- and middle-income countries (LMICs) 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).

Policymakers globally often impose price controls to address concerns about drug affordability and access (Dubois and Lasio, 2018; Kyle, 2025). The welfare effects of price controls are ambiguous when firms have market power or consumers face choice frictions. A canonical literature shows that, in perfectly competitive markets, price controls inevitably lead to undersupply and efficiency losses (e.g., Arrow, 1951; Glaeser and Luttmer, 2003). By contrast, if pharmaceutical companies exercise market power, price controls can lower prices without disrupting supply, thereby improving access to drugs. In standard welfare analysis with fully informed, optimizing consumers, these access gains are unambiguously welfare-improving. However, in healthcare markets, consumers often face choice frictions, such as mistaken beliefs about product quality (Arrow, 1963). In such settings, welfare assessments based solely on revealed preference can be misleading—an important issue that remains largely unexplored in the literature on price controls. For example, a consumer who switches to a branded drug after a price cut could be worse off if they overvalue the brand and should have remained on a cheaper, equally effective generic product.

In this paper, we characterize 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 on the choices of experts 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 such settings: a lack of reliable data on product quality. Finally, we develop and estimate a model of demand and supply to characterize preexisting market failures, 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, where a brand is a distinct name used by different firms to sell the *same* drug. By design, 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 had triple the market share.

We first estimate the effects of the Indian policy on drug 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 ceilings and a 5% price decrease for brands below the price ceilings, suggesting that the policy reduced prices 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 6%

increase in the consumption of regulated drugs, evidencing market expansion. On average, we do not find meaningful changes in the entry or exit of existing drug products or in the launch of new drugs in India within six years after the policy.[1] Therefore, the typical concern that price controls reduce the supply of regulated products does not appear to be a major issue.

Do these findings imply that the Indian price control policy improved welfare? The answer is yes if consumers' brand preferences align with their true utility. Brand preferences could reflect true quality differences: unlike in most high-income countries, India's lax regulation of pharmaceutical manufacturing may not filter out substandard brands. On the other hand, consumers may also favor expensive brands over cheaper but equally effective alternatives because of imperfect information (Bronnenberg et al., 2015) or deference to informal and poorly trained physicians (Das et al., 2022), who may also be influenced by pharmaceutical marketing (Narendran and Narendranathan, 2013). These information and agency issues, which we refer to as choice frictions, imply that observed choices may not reflect true utility. If so, a standard welfare analysis could be inaccurate or even misleading (Bernheim and Rangel, 2005). To accurately assess the welfare effects of the policy, we need alternative, credible measures of true utility.

We use a sophisticated shopper approach, following the spirit of Bronnenberg et al. (2015), to measure the true utility of different brands. We surveyed 617 licensed physicians, recording the brands they have chosen for their *own* treatment. In healthcare markets, physicians are likely the group of consumers with the best possible information about product quality. We restrict our sample to licensed physicians who are demonstrably well-informed across several objective metrics. Moreover, physicians' choices for their own use are not distorted by agency issues. Accordingly, we interpret these expert choices as reflecting their true utility, conditional on other factors — such as price sensitivities and treatment match values — that also affect drug choices.

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, such as those with FDA approval to export to the U.S., and rarely select 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.

To validate the sophisticated shopper approach, we conducted laboratory tests in India. We sampled both the cheaper domestic brands that doctors in our survey buy and the multinational brands popular among consumers. Using two standard tests, uniformity of content and dissolution, we checked whether doctors who switch to cheaper brands sacrifice biochemical quality. We find that the domestic brands are chemically equivalent to the more expensive multinational brands. For example, Ziram and Cardace are, based on our tests, chemically indistinguishable.

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

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

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.

Our estimates reveal significant market power, with most firms charging prices 2 to 10 times their estimated marginal costs. Notably, markups remain high despite the large number of brands per drug. Consumers perceive quality differences between brands, and this perception—combined with heterogeneity in willingness to pay for quality—gives rise to market power. Consistent with our descriptive evidence, consumers systematically overvalue expensive multinational brands. Choice frictions inflate perceived quality differences beyond true differences, thereby exacerbating market power.

We first use the model to quantify the welfare effects of the Indian policy under revealed preference, following previous empirical studies of price controls (Glaeser and Luttmer, 2003; Davis and Kilian, 2011; Cuesta and Sepúlveda, 2021). Given high markups, the Indian policy effectively reduced prices without triggering many product exits, reducing costs for inframarginal consumers and improving access for marginal consumers. Under revealed preference, consumer surplus increases by between \$0.74 and \$4.93 per consumer per year. In most markets, the policy increases total social welfare by correcting monopoly distortions. A notable exception is the diabetes market, where the exit of a highly valued product reduced social welfare by \$1.20 per consumer, highlighting a common downside of price controls. For context, the average consumer spent \$54.90 on statins, which constituted 9% of the median household's consumption budget.[2] Under revealed preference, the Indian policy improved consumer surplus by \$4.93 per consumer—equivalent to 9% of statin costs or roughly 1% of the median consumption budget.

Once we account for choice frictions, the gain in consumer surplus is 30% smaller. Lower prices still transfer surplus from firms to inframarginal consumers. However, 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. These substitutions towards overvalued products, along with occasional product exits, result in an efficiency loss of up to \$2.55 per consumer per year. These results highlight that the interaction between market power and choice frictions is crucial for evaluating price controls. Market power allows firms to charge high markups for overvalued products, which act as a *de facto* "corrective tax" that limits their overconsumption (Griffith et al., 2022; Conlon and Rao, 2023). By lowering this corrective tax, price controls unintentionally reduce total welfare even with relatively minimal supply-side disruptions.

Next, we evaluate alternative designs of price controls. In the absence of choice frictions, the "optimal" drug-level price ceiling balances the trade-off between reducing markups and avoiding product exits. We find that price ceilings near the median brand price perform best in most markets. However, after accounting for choice frictions, the welfare gains from even the optimal drug-level price ceiling are limited. Any drug-level price ceiling imposes larger price cuts on higher-priced products—precisely those that consumers tend to overvalue. As a result, such policies exacerbate the overconsumption of overvalued products, thereby reducing allocative efficiency. To improve efficiency, regulators can consider more granular, product-level price ceilings based on market primitives. While precisely targeted

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

ceilings may be infeasible due to political and informational constraints, we show that regulators can still achieve meaningful welfare gains by designing such policies with coarse information about costs and choice frictions.

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 between \$0.59 and \$11.0 per consumer. This intervention achieves 78% of the first-best surplus gain in the ACE inhibitors market, where products are similar in true quality and choice frictions are the primary market failure. In other markets, however, substantial product differentiation remains even in the absence of choice frictions, leaving firms with significant market power. As a result, eliminating choice frictions alone yields more modest gains, ranging from 2% to 45% of the first-best. Combining friction reduction with price controls generates much larger welfare improvement, underscoring the promise of policies that jointly address both market failures.

Our paper contributes primarily to three strands of literature. First, we advance the economic analysis of price controls. A canonical body of research establishes that price ceilings distort supply and induce shortages in competitive markets (Olsen, 1972; Raymon, 1983; Deacon and Sonstelie, 1991; Glaeser and Luttmer, 2003; Davis and Kilian, 2011; Diamond et al., 2019). Subsequent work examines price regulations in the presence of a *single* preexisting market failure, notably buyer or seller market power (Card and Krueger, 1994; Staiger et al., 2010; Joskow, 2007; Cuesta and Sepúlveda, 2021). Our contribution is twofold. First, we provide a novel analysis of choice frictions, which are highly prevalent in many markets, especially healthcare. Moreover, we characterize the effects of price controls in the presence of two interacting market failures: imperfect competition and consumer choice frictions. We show that the interaction between these distortions is crucial: evaluating price controls in a framework of imperfect competition alone, without accounting for choice frictions, yields substantially different welfare conclusions. This focus on interacting distortions also connects our work to an emerging literature on policy design under multiple market failures (Griffith et al., 2022; Conlon and Rao, 2023; Asker et al., 2024; Bates et al., 2025), applying the intuition from the classic "theory of the second best" (Lipsey and Lancaster, 1956).

Second, we contribute to the welfare analysis of regulations in healthcare markets with consumer choice frictions, particularly pharmaceuticals.[3] Consistent with Dubois and Lasio (2018), we find that price regulations induce substitution from generics to branded drugs, which often retain a sizable price premium even under binding price ceilings. The welfare implications of this substitution are ambiguous, depending on whether consumers' brand preferences reflect true quality differences or choice frictions. While prior studies of pharmaceutical regulation acknowledge this ambiguity, they typically abstract from potential choice frictions or provide wide welfare bounds under different assumptions (Song and Barthold, 2018; Carrera and Villas-Boas, 2023; Kortelainen et al., 2023; Janssen, 2023; Atal et al., 2024; Cao et al., 2024; Grennan et al., 2025). We fill this important gap by adapting the "sophisticated shopper" framework of Bronnenberg et al. (2012) to directly quantify choice frictions and incorporate these estimates into a formal welfare analysis.[4] We also provide a new validation of the sophisticated

[3] See Handel and Kolstad (2015); Baicker et al. (2015) for related studies in insurance markets, and Dubois et al. (2018, 2020) for studies in markets for unhealthy foods.

[4] Our approach complements other empirical strategies that leverage laboratory tests (Bate et al., 2011; Bennett and Yin, 2019) or government inspection data (Dean, 2025; Ishitani, 2025) to measure drug quality.

shopper approach by conducting laboratory tests that can measure biochemical quality.

Finally, our study contributes to the growing empirical literature evaluating price regulation in pharmaceutical markets. Our work connects most directly to several recent analyses of the Indian price control policy (Mohapatra and Chatterjee, 2015; Jaikumar et al., 2023; Dean, 2025). While these studies provide valuable prospective analyses and reduced-form evidence on short-term impacts, the policy's long-run equilibrium effects and aggregate welfare consequences remain underexplored. We bridge this gap in two main ways. First, we analyze a broader set of market outcomes over a long time horizon, thereby capturing key equilibrium effects—such as cross-drug substitution, product diffusion, and innovation—that take time to unfold. Second, we develop and estimate a structural equilibrium model that explicitly incorporates our empirical estimates of consumer choice frictions. This enables us to provide the first formal welfare analysis of the Indian policy and evaluate counterfactual alternative regulatory designs. Our comprehensive analysis of this high-stakes policy also speaks to a broader literature that evaluates a range of policy tools in pharmaceutical regulations, such as external reference pricing (Kyle, 2007; Maini and Pammolli, 2020; Dubois et al., 2022), internal reference pricing (Brekke et al., 2011; Herr et al., 2023), centralized bargaining (Barwick et al., 2025), and competitive bidding (Cao et al., 2024).

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. Section 8 concludes.

2 Setting and Data

2.1 The Indian Pharmaceutical Market

Our setting is the Indian pharmaceutical industry, which serves over 1.5 billion people and ranks as the world's third-largest pharmaceutical market by volume. India is also a major pharmaceutical manufacturer, supplying the entire domestic market and 20% of the global generic drug volume, including 45% of generics consumed in the United States (Indian Brand Equity Foundation, 2024).

We define *therapeutic markets* using the fourth level of the World Health Organization (WHO) Anatomical Therapeutic and Chemical classification (ATC-4).[5] Each ATC-4 group consists of one or more *molecules* that treat the same conditions and possess similar biochemical characteristics. A molecule may be sold in multiple doses; we define a *drug* as a specific molecule–dose combination. A *brand* is a distinct proprietary brand name used by manufacturers to market a drug. For example, Ramipril and Enalapril are two molecules in the ACE inhibitor market (C09A). Cardace and Ziram are two brands of the drug Ramipril-5mg, supplied by Sanofi and FDC, respectively.

India hosts more than 1,000 pharmaceutical manufacturers, which can be broadly classified into three groups: multinational, Indian national, and Indian regional companies. Multinational companies are subsidiaries of global pharmaceutical corporations like Sanofi and Pfizer. On average, they manufacture 34 molecules and supply products in every Indian state. Approximately 90% of them also sell at least

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

one molecule in the US. Indian national companies produce an average of 56 molecules and likewise operate nationwide, with roughly a third of them exporting to the US. By contrast, regional firms are much smaller, producing an average of six molecules sold across five Indian states. They do not export to the US and generate substantially lower revenue than their multinational and national counterparts (Supplementary Table B1).

On average, each drug is produced by 15 manufacturers: one multinational, 10 national, and four regional companies. Approximately 97% of manufacturers, including small regional firms, sell their products under a brand name (Supplementary Figure B1); unbranded generics sold under molecule names, which are common in many other countries, are virtually nonexistent in India. Multinational brands are typically more expensive than national or regional brands (Supplementary Figure B2).

Insurance coverage in India is minimal. In 2014–2015, 80% of households had no health insurance (Supplementary Figure B3). 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 financial burden of pharmaceuticals is large, accounting for 70% of all outpatient healthcare expenditures (Government of India, 2015) (See also Supplementary Figures B4a- B5).

Consumers in India typically purchase medications from private retail pharmacies, which are predominantly small, independent "mom-and-pop" operations.[6] Physicians typically prescribe specific brand names, and Indian law requires pharmacies to dispense exactly what is prescribed, including the specified brand name, with no substitution permitted.[7] Despite this regulation, existing studies have documented instances where pharmacists dispense drugs without a valid prescription (Saradamma et al., 2000; Basak and Sathyanarayana, 2012).

Brand Preferences and Quality Consumers in India exhibit strong brand preferences. In Figure 1, we show that more expensive brands command larger market shares than cheaper brands of the same drug on average, indicating a willingness to pay a premium for certain brands.

Brand preferences may reflect actual differences in product quality, which are not reliably screened due to weak regulatory oversight. Quality can vary across brands because of differences in manufacturing practices, input quality, and transportation or storage conditions. Prior to 2017, licenses to manufacture new brands of an existing drug were granted based on visual inspections rather than on clinical bioequivalence tests, which have been standard in the US and Europe since at least the 1990s.[8] Furthermore, there are widespread concerns about the reliability of government inspections.

A recent policy episode prominently highlights these quality concerns in India.[9] In August 2023, regulators proposed a policy that would require physicians to prescribe by generic name rather than brand. The Indian Medical Association opposed the proposal, arguing that it should "be deferred until the government can assure the quality of all drugs manufactured in India" (Malhotra, 2023). The policy proposal was subsequently withdrawn.

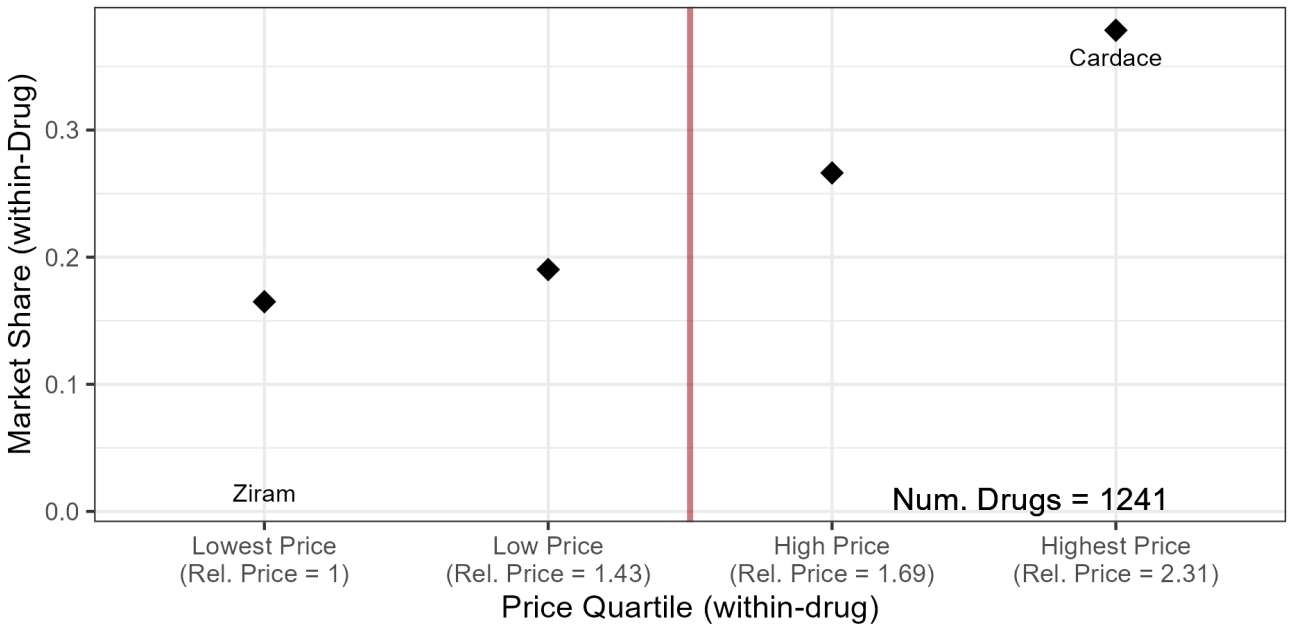
[6] In some rural settings and public health care facilities, physicians directly dispense drugs to patients. These drugs account for less than 10% of the market (Ministry of Health & Family Welfare, 2015-2016).

[7] Specifically, Drugs Rule 65 (11A) stipulates that pharmacists are not allowed to "supply any other preparation, whether containing the same substance or not."

[8] See Drugs and Cosmetics Rules, Tenth Amendment, 2017. The bioequivalence test requirements apply to new drug applications submitted after April 2017 and are not retroactive.

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

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 of all brands in each quartile across N drugs. The market share of a given product is the ratio of the sales of that product to the total sales of that drug. The relative price across different quartiles is denoted on the $x-$axis, where the first quartile is used as a reference. For illustration, the brands Cardace and Ziram of Ramipril-2.5mg are labeled. The vertical line illustrates the price ceiling under the Indian policy.

Brand preferences could also reflect choice frictions such as misinformation and agency issues. Patients may not know that two brands contain the same active ingredient. Physicians may be unaware of cheaper alternatives, as has been shown in the US and Europe (Bronnenberg et al., 2015; Qu et al., 2022; Arrow et al., 2020). Financial incentives from pharmaceutical firms may also influence prescribing behavior (Narendran and Narendranathan, 2013).

2.2 Price Control Policy

Our empirical analysis focuses on the Drug Price Control Order (DPCO) 2013, which granted Indian regulators the authority to set price ceilings for drugs considered essential to the health needs of the Indian population.[10] First announced in October 2013, the DPCO set price ceilings for 550 drugs between 2013 and 2014. The number of drugs under price controls was expanded to 870 in 2015, covering 20% of the Indian pharmaceutical market by sales revenue. Regulated drugs were more likely to treat common conditions, have high sales, be launched before 2005, and have multiple manufacturers (see Supplementary Figures B6–B10).

Price ceilings were set based on pre-policy prices. For drugs with more than five manufacturers, which

[10]Specifically, 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.

constitute 90% of all regulated drugs, the price ceiling was calculated as the unweighted average price of all brands that held at least 1% market share by volume. For drugs with fewer than five manufacturers, regulators applied the average percentage price cut in related therapeutic markets to the drug's pre-policy price. These ceilings remained in effect unless explicitly removed, and the government updated them annually to account for inflation. In Supplementary Figure B11, we present the distribution of prices relative to the statutory price ceiling before the policy was implemented (exposure) and after the policy was fully in place (compliance). A substantial share of products faced binding price ceilings, and most products adhered to the policy—non-compliance was minimal.

The DPCO also granted regulators the authority to add new drugs to the list, including patented drugs. After the 2015 expansion, the list of regulated drugs remained unchanged through 2019, the end of our study period.[11] An amendment in 2019 exempted all patented drugs from price controls for five years.

The DPCO 2013 represented a significant expansion in price regulation. Before this policy, 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 prompted years of deliberation over price control policies. Although an expansion of price controls was widely anticipated, the timing, scope, and method of implementation were not. For simplicity, we refer to the DPCO as "the Indian policy" throughout the paper.

2.3 Data

Our primary data source 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 (Mohapatra and Chatterjee, 2015; Dean, 2025; Cao and Chatterjee, 2022) and extensively by the Indian government for pharmaceutical regulation.[12] The AIOCD data are ideal for studying the Indian policy since regulators set price ceilings based on information in this data.

The AIOCD collects data from a panel of approximately 12,000 stockists, who distribute pharmaceutical products from manufacturers to retail pharmacies. The dataset covers nearly the entire universe of drug sales in private pharmacies across India.[13] We observe sales and prices at the stock-keeping unit (SKU) level, defined by a unique combination of brand, molecule, dosage, and package size. We convert all variables to per-pill units and aggregate them to the brand–molecule–dosage level for analysis.

For our structural analysis, we further convert the unit of measurement from a pill to the defined daily dose (DDD), which represents the standard daily adult maintenance dose for a molecule. This allows us to effectively measure cross-molecule and cross-dosage substitution following standard practices in the literature.[14] We discuss additional details on the sample construction process in Supplementary Appendix A.1.

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

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

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

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

We conducted a large-scale online survey of physicians to assess choice frictions. We also conducted small-scale field surveys of consumers and pharmacists to investigate how choices vary by consumer characteristics and pharmacist knowledge. We defer detailed discussion of these surveys to Section 5.1.

Finally, we utilize several supplementary data sources. We manually collected lists of regulated drugs and price ceilings from government announcements. The National Sample Survey: Health 2014–2015 (NSS Health) provides information on the distribution of healthcare spending, insurance coverage, and education (Government of India, 2015). The Longitudinal Aging Survey of India (LASI) provides microdata on the income, treatment choices, and expenditures of individuals with various diseases. The Pharmaprojects database from Informa 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, then formalize the model, and conclude with a stylized example that illustrates key insights. We bring the model to data in Section 6.

Consumers differ in price sensitivity and choose among pharmaceutical products based on perceived utility and price. Choice frictions create a wedge between true and perceived utility, leading to suboptimal choices. In equilibrium, firms exploit product differentiation and limited competition to charge markups. Producers of high-utility products charge high markups and target price-insensitive consumers. These markups cause price-sensitive consumers to forgo high-utility products that they would have purchased at marginal cost.

Price controls constrain markups, bringing prices closer to marginal cost. This price change affects welfare through two channels. First, lower prices transfer surplus from firms to inframarginal consumers. Second, marginal consumers substitute toward now-cheaper products because they perceive a utility gain. Without choice frictions, such substitution increases consumer surplus and overall welfare by correcting monopoly distortions. However, if consumers overvalue regulated products, the actual welfare gains from switching are smaller than the perceived gains. When choice frictions are sufficiently large, lower prices can even *reduce* consumer surplus.

Beyond pricing, price controls can also influence market participation. A sufficiently low price ceiling induces product exits, thereby reducing both profits and consumer surplus. If marginal costs are positively correlated with product utility and choice frictions are limited, the most valued products are the first to exit, implying greater welfare losses.

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. 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):

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

The term δ_{js} represents the mean time-invariant utility that consumers expect 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 features, 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 also i.i.d. type-1 extreme value, yielding the nested logit model (Cardell, 1997; Berry, 1994). The molecule-level shocks capture heterogeneous match values 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 price p_{jst}, depending on their price sensitivity α_i. The distribution of price sensitivity is denoted by $H_s(\alpha_i)$.[16] 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).

3.1.2 Choice Frictions

Consumers may not choose the brands that provide the highest true utility because of choice frictions. As discussed in Section 2.1, choice frictions may arise from mistaken beliefs or agency issues. Consumers or possibly some poorly informed healthcare providers may have mistaken beliefs about the quality of

[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 Sections D.1, we formulate an extended model of patient and physician choices and show that this abstraction is with limited loss for our analysis.

[16] Given our demand model, firms have market power for two reasons. First, price sensitivity varies between consumers, resulting in differentiation of products with different (vertical) quality. Second, logit shocks create further product differentiation. See Supplementary Section D.2 for an illustration.

different brands (Bronnenberg et al., 2015; Das and Hammer, 2014). Physicians may not know of some cheaper alternatives (Arrow et al., 2020). Financial incentives, such as detailing, can also lead physicians to prescribe expensive 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 and uses δ_{js}^{fr} as a representation of all wedges that prevent consumers from choosing the product with the highest true utility. This parsimonious formulation suffices to quantify the magnitude of choice distortions and assess their implications for the welfare effects of price controls. In Supplementary Section D.1, we derive our formulation from a richer model in which patients and physicians jointly make drug choices based on potentially inaccurate beliefs and distortionary financial incentives, thereby elucidating the microfoundations of our formulation.[17]

Welfare with Choice Frictions The standard welfare measure based on revealed preference is inaccurate when choices reflect distorted perceptions of utility. We address this issue by directly measuring and adjusting for the wedge between perceived 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 make choices based on perceived utility δ, but welfare is evaluated using true utility δ^{true}. The change in consumer surplus from a policy-induced price change to p^{pol} is:

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

Ignoring choice frictions can lead to misleading conclusions about the sign and magnitude of the welfare gains from price controls. Consider the case where the price of product j decreases and a consumer switches to j in response. In the absence of choice frictions, this marginal consumer experiences a welfare gain by revealed preference. However, if this consumer overvalues product j in the first place because of choice frictions (i.e., $\delta_{js}^{\text{fr}} > 0$), the true welfare gain is smaller. If the choice frictions are sufficiently large, consumer welfare can *decrease* because of a price decrease.

[17] 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. In Supplementary Section G.7, we show the sensitivity of our results to different assumptions about the correlation between price sensitivity and choice frictions.

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 expected profits in the second period. In the second period, profit-maximizing firms compete in prices à la Nash–Bertrand, taking consumer preferences, marginal costs, and the set of products as given. Price ceilings can affect both pricing and product availability.

We assume that firms make pricing and exit decisions annually and independently in each state s. For expositional clarity, 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–Bertrand. 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 $\Omega_{jj'} = 1\{\exists f : j \in J_f \text{ and } j' \in J_f\} \frac{\partial \sigma_j(p^{\text{eq}})}{\partial p^{\text{eq}}_{j'}}$.

Under price controls, firms maximize profits subject to price ceilings imposed by the regulator. Let $\bar{p}_j$ denote the price ceiling and λ_j denote the Lagrangian multiplier for product j. The equilibrium prices under the policy, denoted p^{pol}, are characterized by the following conditions:

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

Note that prices change because of two forces. First, the price ceiling becomes binding for products whose pre-policy equilibrium price satisfies $p^{\text{eq}} > \bar{p}$, forcing a price reduction via the complementary slackness condition. Second, for products priced below the ceiling or not subject to regulation, prices may also adjust in response to competitors' price changes.

3.2.2 Product Exit

A firm f is endowed with a set of products $\mathcal{J}_f$ that it can produce.[18] 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 $\mathcal{J}_f \setminus J_f$, where $P(\mathcal{J}_f)$ denotes the power set of $\mathcal{J}_f$.

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

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' profit functions. An equilibrium is a set of product offerings J^{eq} such that $J^*(J_{-f}^{\text{eq}}) = J_f^{\text{eq}}$ for all firms f. Intuitively, firms will discontinue products whose marginal costs exceed the price ceiling, as well as products that, when priced below the ceiling, would yield net negative profits by cannibalizing sales of other products in the firm's portfolio. Although multiple equilibria are theoretically possible, we consistently find a unique equilibrium in our empirical analysis. See Section 7 and Supplementary Section G.5 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 over a decade ago, and fixed costs have likely been fully amortized. Fixed costs are commonly included in the model to rationalize observed exits (Berry and Reiss, 2007). We show that the exit patterns predicted by our model closely match those observed in the data, validating that our model fits the data well despite this restriction.

3.2.3 Discussion of Other Supply-Side Margins

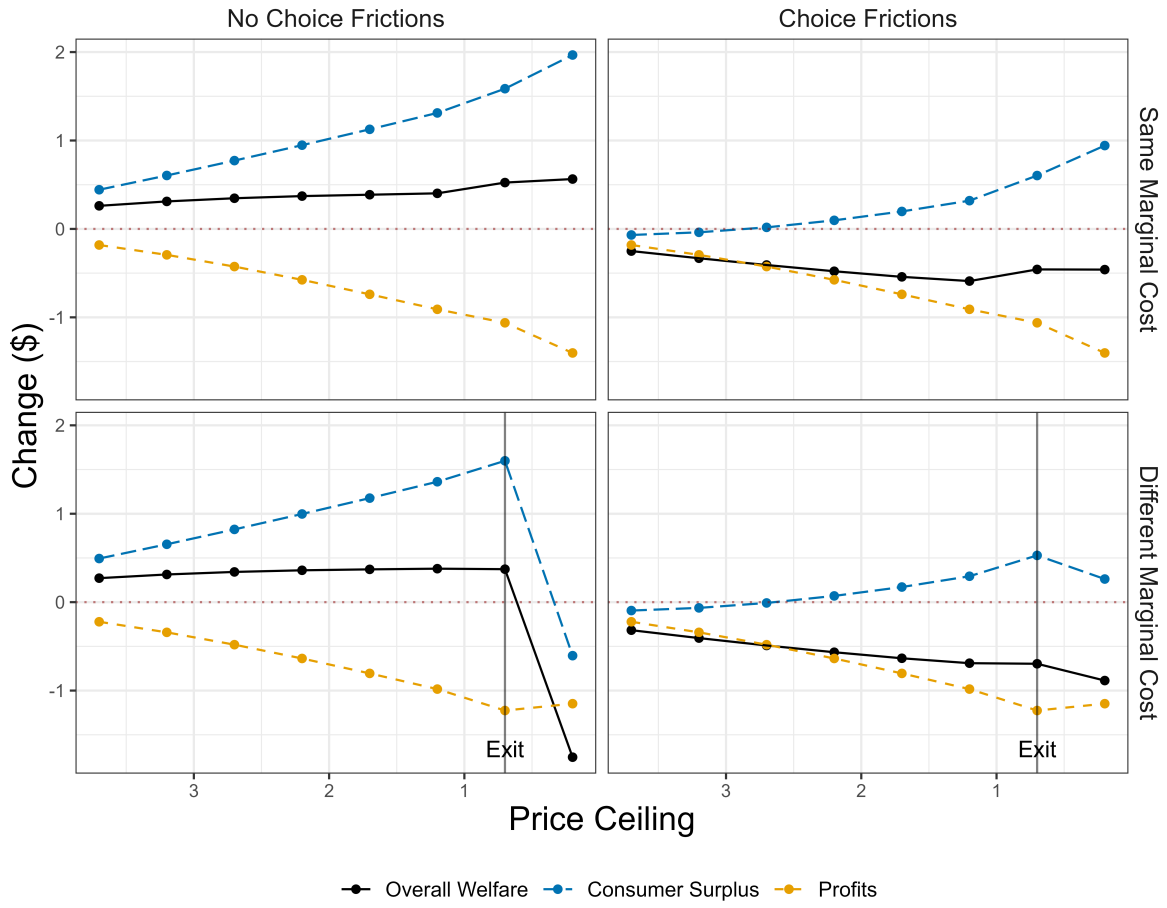
We do not model the entry of new brands because they are empirically rare in our setting. Entries of new brands were uncommon before the policy, and we show in Section 4.4 that entry rates remained unchanged following price controls. Similarly, we do not model the effect of price controls on the launch of new molecules, given the transient changes we find in Section 4.5.

We also treat product quality δ_j^{true} and marginal costs mc_j as exogenous in our model. While price controls could, in principle, incentivize firms to reduce quality to lower costs, this concern is mitigated in our context. The Indian policy primarily targets high-priced brands, whose manufacturers often export to other countries such as the U.S., where stringent quality standards apply. Compromising quality in the domestic market risks tarnishing the integrity of the firm's global supply chain and brand image, posing a threat to profits from these lucrative, quality-sensitive export markets. Our survey evidence further supports this assumption: only 10% of the physicians in our survey report any perceived deterioration of product quality following the price control policy (Supplementary Figure F2).

3.3 Stylized Illustration: Welfare Effects of Price Controls

We present a stylized example to illustrate the key economic mechanisms mediating the welfare effects of price controls. 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 includes one *h*igh brand and three *l*ow brands produced by a different firm. Let $\delta_l = \delta_l^{\text{true}} = 0$ and $mc_l = 0$ for all low brands. The high brand has perceived utility $\delta_h = 4 = \delta_h^{\text{true}} + \delta_h^{\text{fr}}$. The marginal cost of the high brand mc_h and choice frictions $\delta_h^{\text{fr}} = 4 - \delta_h^{\text{true}}$ are free parameters.

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.

Firms can charge prices above marginal cost because of product differentiation and limited competition. Brand h commands market power because it offers higher perceived utility and has no close substitutes, allowing it to charge a markup in equilibrium.

We illustrate the effect of a price ceiling $0 < \overline{p} < p_h^{\text{eq}}$ under four scenarios that vary in marginal cost mc_h and choice frictions δ_h^{fr}. In the first case, brand h has higher true utility, and all brands have the same marginal 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 marginal cost with true quality differences ($\delta_h^{\text{fr}} = 0, mc_h = 0.5$) and without true quality differences ($\delta_h^{\text{fr}} = 4, mc_h = 0.5$), 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, without inducing any product exits. Most price-insensitive consumers continue to

choose brand h and benefit from the lower prices. This welfare improvement is exactly offset by the reduction in firm profits, implying a transfer of welfare from firms to inframarginal consumers. The price ceiling also induces some price-sensitive consumers to switch from l to h.[19] In the absence of choice frictions, these marginal consumers are better off by revealed preference. In this case, the price ceiling corrects 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 products have the same true quality, although consumers mistakenly 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 implications for marginal consumers. Although these consumers perceive a surplus gain from switching to h (and thus choose to switch), they are in fact worse-off over a wide range of price ceilings: brand h, even at the regulated price, remains more expensive than the low brands l that offer the same true quality. At some price ceilings, this welfare loss for marginal consumers even outweighs the welfare gains for inframarginal consumers, resulting in a net decline in consumer surplus (top-right panel of Figure 2). With firm profits also falling, total social welfare decreases under any binding price ceiling.

A key insight is that distortions from market power and choice frictions counteract each other in equilibrium: high prices act as a *de facto* "corrective tax" that mitigates the overconsumption of brand h. By attempting to correct market power, price controls inadvertently offset this corrective force and exacerbate inefficiencies caused by choice frictions, ultimately reducing overall welfare.

Case 3 In the third case, brand h has higher true quality and is costlier to produce. Its high equilibrium price reflects the cost of providing a truly high-quality product. Price ceilings above mc_h benefit consumers and improve social welfare, as they do in Case 1. However, a price ceiling below mc_h would force brand h to exit. The exit of a high-quality product reduces firm profits, consumer surplus, and overall welfare, as shown in the bottom-left panel of Figure 2.

Case 4 Last, we consider a case where brand 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 limited impact on consumer surplus because of the availability of other products with similar quality. In fact, surplus may *increase* for some consumers, as the exit of brand h prevents them from overpaying for a product they mistakenly perceive as superior.

This simple example shows that the welfare effects of price ceilings depend crucially on three key economic primitives: markups, choice frictions, and the correlation between true product utility and marginal cost. We will carefully recover these primitives when we take the model to data in Section 6.

[19] 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.

4 Effect of the Indian Policy on Market Outcomes

4.1 Empirical Strategy

We estimate the effects of the Indian policy on key market outcomes using an event study design. Conceptually, we compare changes in outcomes for regulated products relative to unregulated products following the implementation of the policy. Treated units are regulated products, which we further classify as "Above Price Ceiling" or "Below Price Ceiling" based on their pre-policy prices. Control units are unregulated products that do not share an ATC-4 group with any regulated product. We exclude unregulated products within the same ATC-4 group as a regulated product because of potential therapeutic substitutions in equilibrium. In Supplementary Table B2, 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 between treated and control products in the absence of price controls, and (2) no anticipatory effects. We will assess the validity of assumption (1) by testing for pretrends in the event-study estimates. Before doing so, we first present evidence supporting assumption (2).

No Anticipatory Effects For firms to respond strategically in anticipation of the Indian policy, they would have needed advance knowledge of its timing, scope, and method of implementation. Although the prospect of expanded price regulation was widely discussed in Parliament and reported in the media, the method of setting price ceilings based on average pre-policy prices represented a significant departure from the historical cost-plus framework and was largely unexpected. As a result, firms had limited opportunity to adjust prices strategically in advance of the policy.

We empirically assess this assumption using a placebo exercise. For each month in our panel, we simulate the price ceiling based on drug prices in that month. If firms had attempted to increase the price ceiling by raising prices beforehand, we would expect to see an increase in the simulated ceilings for the regulated drugs before the policy was implemented. In Supplementary Figure B13, we show that there is no such trend, suggesting that firms did not strategically adjust their prices in anticipation of the policy.

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.[20] After the policy was phased in, prices of regulated products above the 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 fell below 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*. Within each drug, brands in higher pre-policy price deciles experienced larger price reductions. These results show that the policy generated rich cross-brand variation in price changes based on pre-policy price levels.

Figure 4a shows that sales of regulated products above the price ceiling increased by 36% following the policy. 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. Had this pretrend persisted post-policy, our estimates would be downward biased. In Supplementary Figure B14, we show that the increases in sales are the largest for the brands with the highest pre-policy prices.

4.3 Results: Market Expansion and Cross-Drug Substitutions

Next, we measure the impact of the policy on drug-level outcomes. Recall that the regulated drugs are considered essential for public health. If the policy improved access to these essential medicines, it would have yielded significant public health benefits. For this analysis, we aggregate our sample to the drug level and compare outcomes for regulated drugs and control drugs using the same event study framework.

Sales of the regulated drugs increased by 6% (Figure 4b) following the price changes documented above (see also Supplementary Figure B15). We also find a 50% reduction in the sales of unregulated drugs within the same ATC-4 as at least one regulated drug (Supplementary Figure B16).[21] These results show that price controls led to substitution across therapeutic alternatives and expanded access to essential medicines. Whereas within-molecule substitutions occurred almost immediately after implementation, it took over two years for cross-molecule substitutions and market expansion to unfold.

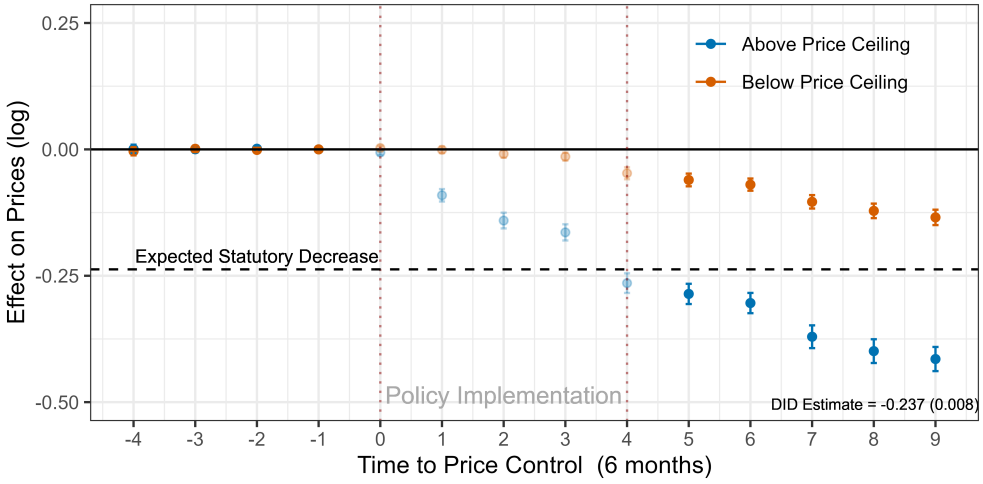
4.4 Results: Exit, Entry, and Detailing

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 led to a small reduction of 0.25 brands per regulated drug, corresponding to a 1.7% decline (Figure 4c). This reduction is driven by a slight increase in product exits (Supplementary Figure B17), while we observe no significant change in new brand entry (Supplementary Figure B18). While the overall impact on product availability is negligible, we do observe policy-induced product exits in 17.8% of therapeutic markets (Supplementary Figure B19), where they could have significant welfare implications.

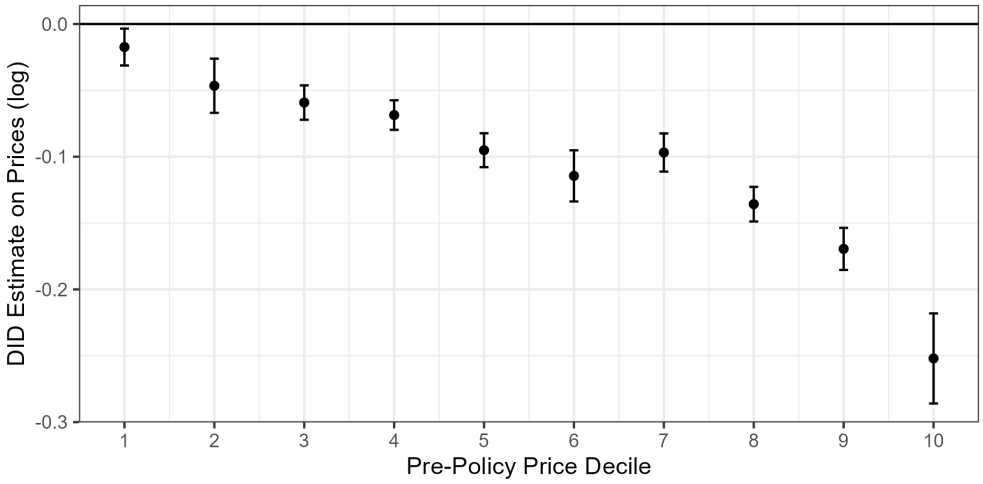
[20] The pretrends are estimated and are *not* mechanically set to zero, as the figure may suggest. The figure includes error bars for the pretrends, but they are not visually discernible.

[21] Unregulated drugs typically have much lower baseline sales, as shown in Supplementary Figure B7.

Figure 3: Effect of the Indian Policy on Prices



(a) Event Study Estimates



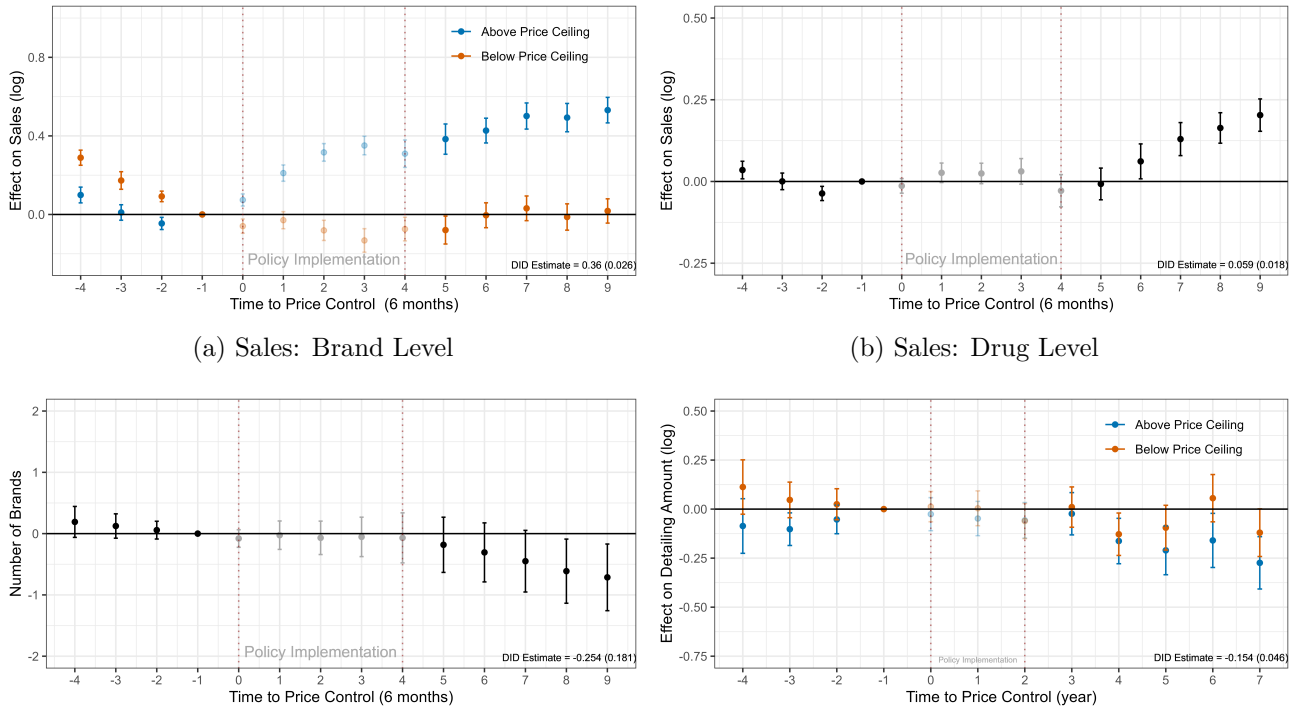
(b) Difference-in-Differences Estimates by Pre-Policy Price Levels

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.

We also estimate the impact of the Indian policy on advertising to physicians ("detailing"), similar to contemporaneous research in the U.S. context (Hristakeva et al., 2024). We use the IQVIA Channel-Dynamics dataset, a leading resource of market intelligence that records monthly detailing expenditures at the firm–molecule–channel level in India.[22]

We find no significant change in detailing on the extensive margin (Supplementary Figure B20). On the intensive margin, detailing expenditures declined by 16% for regulated products priced above the ceiling (Figure 4d). We note that detailing levels in this market segment were already low: the average firm spent about \$6,500 on detailing per drug–year, so the observed decline corresponds to only about \$1,000 in absolute terms. Therefore, despite the sizable percentage change, the economic impact is likely minimal.[23]

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



(a) Sales: Brand Level

(b) Sales: Drug Level

(c) Number of Brands per Drug

(d) Detailing (Intensive Margin)

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 brands per drug (Panel c), and the amount of detailing per year (Panel d). The x-axis denotes the time relative to the implementation of the price control. The y-axis shows the ATT estimates with 95% confidence intervals.

4.5 Results: Effect on New Molecules

Price controls may disincentivize pharmaceutical innovation, creating a potential trade-off between short-run affordability and long-run access to new treatments (Bryan and Williams, 2021). While this trade-off

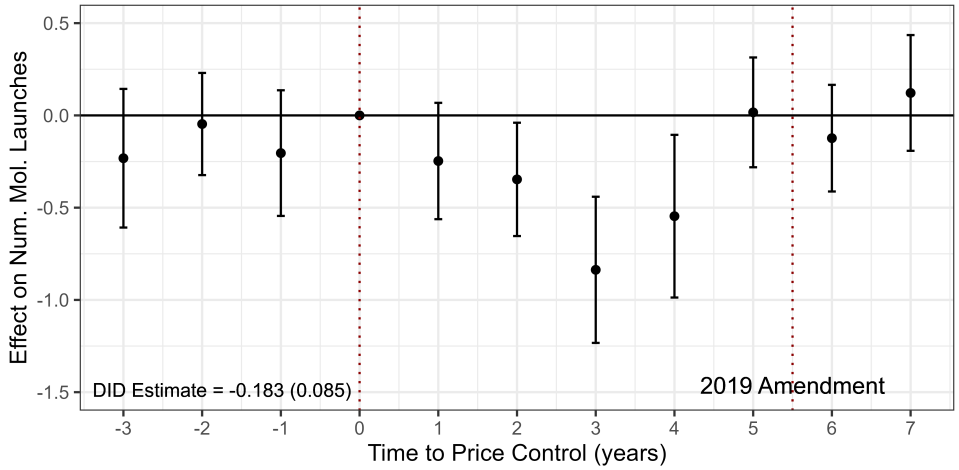
[22] See Supplementary Section A.2.2 for a complete description of the data.

[23] In Supplementary Figure B12, we describe the dynamics in detailing spending. We find that detailing peaks in the first three to four years after a molecule's launch, followed by a steep decline and minimal spending in later years. This is consistent with the low level of detailing spending for regulated products when the Indian policy took effect, as most of these drugs had been on the market for many years.

is central to policy 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 on the impact of the Indian policy on drug development and diffusion. A full discussion of the data, estimation procedure, and results is provided in Supplementary Section B.4.

To empirically assess this trade-off, we use the Pharmaprojects dataset to estimate the effect of the Indian policy on the launch of new molecules in both the Indian and global markets. Specifically, we compare trends in innovative activity before and after the policy between firms that specialize in therapeutic markets with varying degrees of exposure to price controls in India.

Figure 5: The Effect of the Indian Policy on New Molecule Launches in India



Notes: The figure presents the dynamic effects of the price control policy on the approval of new molecules in India. The $x-$axis is the time from when the price control was implemented. The $y-$axis shows the ATE estimates with 95% confidence intervals. Each observation is a firm-year pair. The standard errors are clustered at the firm level.

As shown in Figure 5, we find a gradual decline in the launch of new molecules in India following the policy, reaching a peak reduction of 0.8 new molecules per firm in 2017. The risk of being included under price controls likely discouraged pharmaceutical companies from introducing new products into the Indian market. However, this effect was short-lived and had completely dissipated by 2019. The 2019 amendment, which granted a five-year exemption from price controls for patented drugs, appears to have effectively reversed this modest decline in drug diffusion.

Beyond India, we find no economically or statistically significant impact of the policy on the launch of new molecules or initiation of new clinical trials worldwide (Supplementary Figures B23 and B25). Similarly, the Indian policy had minimal impact on the stock prices or research and development expenditures for publicly listed pharmaceutical firms (Supplementary Figure B26).[24]

[24]The majority of publicly listed pharmaceutical companies in our data are either multinational corporations or Indian national companies that export to the U.S. Their stock market performance therefore reflects profit outlook from the global market, rather than from the Indian market alone.

5 Descriptive Evidence on Choice Frictions

As the model illustrates, the welfare effects of price controls depend crucially on the presence and magnitude of choice frictions. Unfortunately, there are no systematic and comprehensive estimates of brand-level biochemical quality or the extent of choice frictions in the Indian pharmaceutical market.[25]

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 do not experience choice frictions and make choices based on true utility δ^{true} instead of δ. The difference in choices between these consumers and the general population, conditional on demographics and preferences, captures the extent of choice frictions. In healthcare, physicians are natural candidates for the role of sophisticated shoppers. They likely have the best possible information, and their choices for themselves are not subject to agency problems. Recent studies affirm physicians' expertise in making effective treatment choices – for example, in their effective statin choices and the choice of medications to prevent emergency department visits (Kakani et al., 2025; Carrera and Skipper, 2025).

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

5.1 Physician Survey

Recruitment For our survey, we recruited Indian physicians who met two eligibility criteria: (1) they are licensed and registered with a legitimate medical board in India, and (2) they are actively practicing. This focus on licensed physicians is particularly important in the Indian context, where poorly trained and informal providers remain prevalent (Das and Hammer, 2014). We sourced physician contact information from a large healthcare marketing company in India that regularly verifies its database to exclude unlicensed physicians. In addition, we manually screened out respondents who reported not being registered with a medical board or listed a nonexistent state board.

We invited 67,902 physicians to participate by email and text message. The invitation stated that the study aimed to understand physicians' healthcare choices, that it had received IRB approval, and that responses would be anonymous and used solely for academic purposes. Respondents were offered Rs. 1,000 ($\approx$ \$14) as compensation for their time upon completion of the survey.[26]

Our final sample consists of 617 physicians. Of the 67,902 invited, 981 started the survey, and 857 were verified to be licensed practitioners. Among these, 299 had used medications in at least one of the five therapeutic markets included in our structural analysis and were automatically enrolled. We randomly selected an additional 318 physicians from the remaining eligible pool to complete the survey for a randomly selected therapeutic market.[27]

[25] Both academic studies and government inspections have been limited in their coverage. Many physicians and 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 E.

[26] This amount corresponds to the upper percentile of consultation fees charged by physicians in India.

[27] Due to budgetary constraints, we included only a subset of physicians who did not report personal use of the medications.

Survey Instrument Our survey consists of three main components. In the first section, physicians 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 provide a qualitative explanation for their drug choice.

The second section presents two hypothetical choice scenarios. First, we ask the physicians 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 choice if their preferred brand were unavailable. These questions mimic the discrete choice experiments (DCEs) commonly used in health economics to evaluate take-up of new interventions (de Bekker-Grob et al., 2012) and in labor economics to estimate the value of workforce amenities (Mas and Pallais, 2017; Caldwell et al., 2025).

The third section assesses physician knowledge. We collected information on several professional attributes, including the ranking of their medical school, practice type, the number of patients treated per week, and total hours worked per week. Crucially, we also included two clinical knowledge questions adapted from materials used in U.S. medical board examinations.[28] Finally, we collected additional demographic information such as annual income.[29]

5.2 Sample Characteristics

In Supplementary Table F1, we present descriptive statistics for the physicians in our survey sample. The average respondent was 28 years old, identified as general practitioners or primary care physicians (69%), reported working in private healthcare facilities (72%), reported working at least 40 hours per week (68%), and correctly answered the knowledge check question (65%).

We benchmark our sample against two prior physician surveys in India: Das and Hammer (2007) and Das et al. (2022).[30] The first study surveys providers in urban Delhi ($N = 205$), and the second is a representative survey of rural providers in 19 states ($N = 3,473$). Compared to these studies, our sample consists entirely of formally trained physicians (100% vs. less than 55%). Our physicians are younger (average age 28 vs. 40–44), less likely to be male (63% vs. 79%–88%), and more likely to have a postgraduate degree (36% vs. 28.5%). Importantly, over 65% of our respondents answered challenging medical questions correctly, while only 30% of the physicians in the other studies could answer basic medical questions.

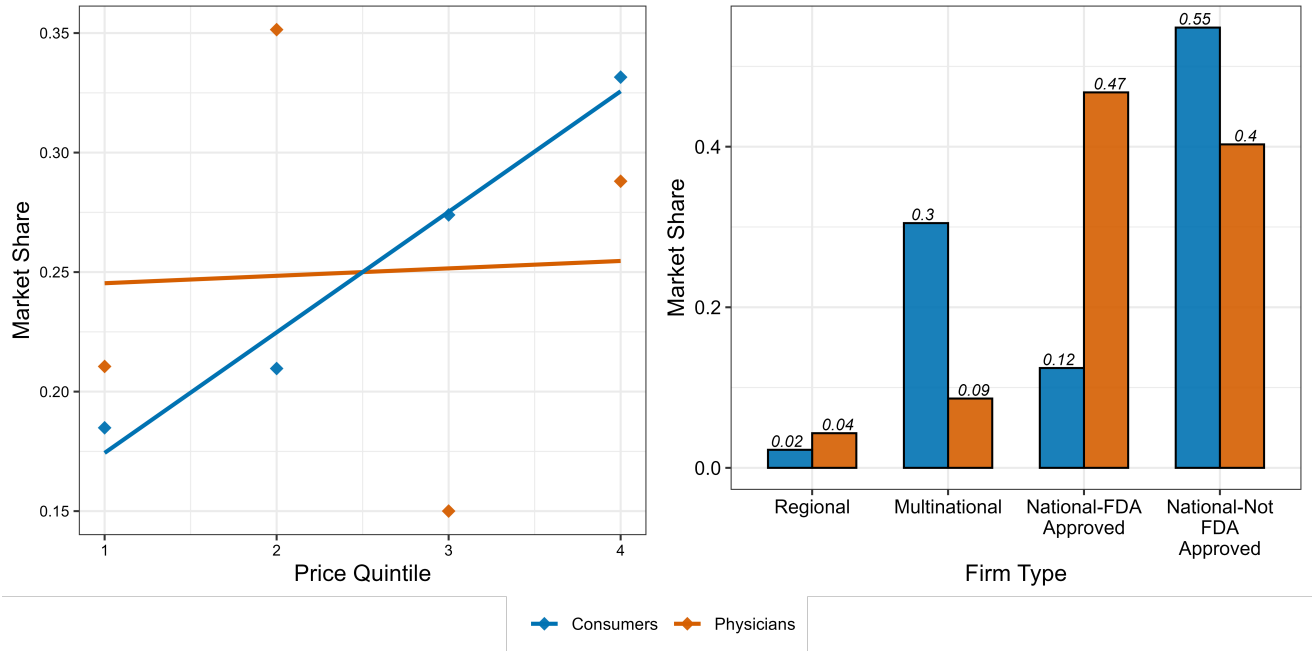
This difference is intentional. We deliberately oversample formally trained and highly educated physicians to identify a group whose choices can plausibly serve as a normative benchmark. Therefore, it is desirable for us to select knowledgeable physicians who are *unrepresentative* of the average Indian physician, many of whom lack formal training and proper medical knowledge, as documented in previous studies (Das et al., 2022).

5.3 Comparison of Patient and Physician Choices

In the left panel of Figure 6, we show that the physicians in our sample are less likely to buy high-priced brands than consumers. The right panel shows that, unlike consumers, physicians rarely choose

[28] We selected and validated these questions in consultation with physicians in both the U.S. and India.
[29] A copy of the survey instrument can be accessed at https://kellogg.qualtrics.com/jfe/form/SV_2mB7NknJD3YiH3g.
[30] We cannot directly evaluate the representativeness of our sample as there is no census of medical providers in India.

Figure 6: 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.

multinational brands. Instead, they exhibit a consistent preference for *specific* Indian manufacturers, such as Cipla and Mankind, across multiple molecules and therapeutic markets. Notably, physicians tend to prefer Indian firms that are approved by the U.S. Food and Drug Administration (FDA) to export to the U.S. These patterns suggest that the sampled physicians, drawing on their training and experience, are able to identify high-quality domestic brands among the cacophony of different options. In contrast, consumers lack the information or expertise to distinguish among options and instead rely on coarse heuristics such as price or multinational status as proxies for quality.

Our qualitative questions provide additional insights into the factors underlying physicians' brand choices. Specifically, physicians frequently report selecting their preferred brand because of its high quality or the firm's established reputation for quality (78%), as well as the brand's local availability in pharmacies (56%)(Supplementary Figure F1). Taken together, these responses suggest that the physicians' choices reflect their beliefs about biochemical quality and ease of access, both of which are welfare-relevant inputs in our normative framework. Physician choices for *themselves* are not influenced by factors like "Interaction with company representative"(7%) that might create agency issues in patient care.

To further examine how choices vary with physician knowledge, we exploit multiple measures of expertise collected in our survey. In Supplementary Tables F2 and F3, we show that the patterns of choices remain similar when we focus on the most knowledgeable physicians — specifically, physicians who attended top-ranked medical schools, work full-time or in leading hospitals, or correctly answered both clinical knowledge questions. As long as these most knowledgeable physicians are not subject to

choice frictions, the choices documented in our survey would be similarly free of such frictions.

We emphasize that these descriptive patterns alone do not yield estimates of choice frictions δ^{fr} because they do not account for other determinants of drug choices, such as income, that likely differ between physicians and consumers. In Section 6.2, we formally incorporate the survey responses into our empirical model to estimate choice frictions while controlling for other relevant factors.

5.4 Taking Stock

We find that the Indian policy reduced drug prices, increased the utilization of regulated drugs, and had minimal impact on product exit and entry. These outcomes suggest that price controls mitigated monopoly distortions and generated welfare gains. Given that the regulated drugs were considered essential for public health, increased utilization may also yield substantial health benefits.

However, our analysis also reveals that price caps primarily affected high-priced brands — precisely the products physicians in our survey typically do *not* choose for themselves. The main behavioral response to the policy was a shift in consumer demand away from inexpensive generics toward these now-cheaper but still costlier brands. If consumers overvalue such brands, as our physician survey suggests, this substitution may not improve consumer welfare.

While these descriptive findings offer valuable insight into the benefits and costs of the Indian policy, further analysis is needed to precisely quantify its welfare effects and evaluate alternative policy designs. Importantly, we still need to measure choice frictions and characterize how different market primitives shape heterogeneity in the policy's impacts on market outcomes and social welfare. We turn to our structural model to address these key questions.

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 a substantial portion of the drugs regulated by the Indian policy. Supplementary Section G.1 details our selection criteria, discusses specific exclusions, and presents descriptive statistics for each market (Supplementary Table G1). We estimate the model separately for each therapeutic market. For clarity of exposition, we discuss the estimation procedure as if applied to a single market, and later present the results by market.

6.1 Revealed Preference Demand and Supply

In this section, we describe the estimation of the revealed-preference demand and supply parameters, deferring the details of our estimates of choice frictions to Section 6.2. Our immediate goal is to recover the distribution of price sensitivity $H_s(\alpha_i)$, the perceived product utility δ, the nesting parameter ρ, and marginal costs mc. The estimation proceeds in three steps. First, we specify a parametric form for the distribution of price sensitivity, $H_s(\alpha_i)$. Second, we estimate the demand-side parameters by

matching the observed changes in product market shares resulting from policy-induced price changes, using a two-step Generalized Method of Moments (GMM) procedure (Berry et al., 1995). Third, we recover marginal costs by inverting the Nash–Bertrand first-order conditions that characterize firms' optimal pricing strategies, as defined in Equation 3.4.

We do not incorporate information on product exit into the estimation, as our model does not include the fixed costs of carrying a product. We will assess how well our model replicates the observed exit patterns when we discuss estimation results.

Econometric Specification 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.3, we derive this specification from a microfounded model in which consumers maximize a Cobb–Douglas utility function over health and non-health consumption subject to a budget constraint. This parametric specification is similar to standard approaches in industrial organization and health economics (e.g., Berry et al., 1995; Finkelstein et al., 2019).

Given this specification, the distribution of price sensitivity depends on the joint distribution of income and health status, $F_s(\theta_i, y_i)$, the price sensitivity of consumers in poor health, α_p, and that of consumers in good health, α_g.

Distribution of Income and Health Status We estimate the share of consumers in good health, $Pr_s(\theta_i = g)$, and the distribution of income conditional on health status, assuming $\log(y_i|\theta_i) \sim \mathcal{N}(\mu_{\theta_i s}, v^2_{\theta_i s})$. These parameters are calibrated to match the empirical distribution observed in LASI.[31] This nationally representative health survey, conducted between April 2017 and December 2018, provides microdata on individuals' disease history in the current and past year, self-reported health status, and income.[32] Supplementary Figure G1 presents the empirical distribution of income by health status.

Demand Parameters Next, we estimate the demand parameters $\theta^d = \{\alpha_p, \alpha_g, \rho\}$, where α_p and α_g denote the price sensitivity of consumers in poor and good health, respectively, and ρ captures the relative importance of molecule-level preference shocks. Estimation follows the GMM procedure of Berry et al. (1995) and solves:

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

where $\Delta\xi_{jst} = \xi_{jst} - \xi_{jst=2013}$ is the change in unobserved demand shocks relative to the policy implementation year, Z_{jst} are instruments, X_{jst} are controls, and W is the optimal weighting matrix from the two-step GMM. Given a value for θ^d, we recover $\delta_{js} + \xi_{jst}$ using a standard contraction mapping to match model-predicted and observed market shares. We then take fixed differences to compute $\Delta\xi_{jst}(\theta^d)$ and minimize the sample analog of the objective function.

The main threat to identification is that post-policy changes in sales and prices may be confounded by unobserved demand shocks. To address this, we construct simulated instruments Z_{jst} based on the

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

[32] Following standard practice in LMIC contexts, we proxy income using daily consumer expenditure due to measurement challenges associated with direct income reporting (Poirier, 2024).

statutory price changes mandated by the Indian policy. These instruments exploit plausibly exogenous variation in the intensity of price controls, which reflects pre-policy price dispersion among regulated products. We argue that these instruments are orthogonal to unobserved demand shocks, so that differential post-policy sales responses to the simulated price cuts provide the basis for identification.

We simulate the statutory price changes by applying the pricing rule to pre-policy data. Formally, let $T_{js} = 1\{js \text{ is price controlled}\}$ indicate whether drug j in state s is regulated. Recall that the price ceiling is set at the molecule-level average price $\overline{p_m}$, which we compute using the pre-policy prices from 2011.[33] The simulated price change for product js is given by $E_{js} = \max(p_{js} - \overline{p_m}, 0)$.

We construct three instruments for a product js based on simulated policy-induced price changes for the focal product and its competitors. The first instrument captures a product's own statutory price change: $Z_{1jst} = 1\{t > 2013\} \times T_{js} \times E_{js}$. The second instrument, Z_{2jst}, involves the average simulated price change of other products of the same molecule. To capture heterogeneity in cross-product substitution, we interact this instrument with discrete bins of the focal product's pre-policy price levels, denoted G_{js}. Specifically, $G_{js} = h$ if $p_{js} > 1.1\overline{p_m}$ (high-priced), $G_{js} = l$ if $p_{js} < 0.9\overline{p_m}$ (low-priced), and $G_{js} = m$ otherwise (medium priced).[34] This interaction accounts for differential responses to competitor price changes based on a product's initial price position. The third instrument, Z_{3jst}, is the average simulated price changes of *other* molecules in the same therapeutic market, capturing therapeutic substitutions across molecules.[35]

Supplementary Section G.3 provides an illustrative example showing how each moment condition identifies specific demand parameters and how our instruments generate sufficient variation for identification. We briefly discuss the high-level intuition here. The correlation between a product's own price change (Z_{1jst}) and its sales change identifies the average price sensitivity. The interaction of rivals' price changes with pre-policy price levels (Z_{2jst}) identifies heterogeneity in price sensitivity: greater dispersion in price sensitivity implies that price reductions for formerly high-priced products disproportionally divert sales from similarly high-priced competitors. 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 post-policy changes in unobserved demand shocks are conditionally independent of the simulated price reductions: $\mathbf{E}\left(\Delta\xi_{jst}|Z_{jst}, \gamma_{st}, \gamma_{T_{js}G_{js}t}\right) = 0$ (Berry and Haile, 2014).[36] We include regulation status × price level × year fixed effects $\gamma_{T_{js}G_{js}t}$ as controls. These controls account for time-varying confounders affecting all regulated products, such as increased consumer awareness of regulated products after the policy announcement. Thus, identification relies on variation in the *magnitude* of the policy-induced price changes within each price bin instead of simple differences in regulatory status. We also include state–year fixed effects γ_{st} to control for macroeconomic trends in different states.

[33] 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.

[34] Firms typically charge a uniform price for a product across all regions. Minor regional variation in G_{js} can arise due to differences in choice sets.

[35] 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 $Z_{3jst} = 1\{t > 2013\} \times \sum_{j' \neq j} 1\{m(j') \neq m(j)\} E_{j's} s_{j's}$, where $m(j)$ denotes the molecule of product j.

[36] 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.

Our event study and placebo analyses validate the exclusion restriction. We find no pretrends in prices prior to the 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 in 2012, 2016, and 2019. The results mitigate concerns about serial correlation in unobservables: the simulated price changes are strongly correlated with observed price declines during the policy rollout ($t = 2016$), but not before the policy ($t = 2012$) or after its full implementation ($t = 2019$). Furthermore, a post-estimation diagnostic shows minimal correlation between simulated price changes and changes in the empirical analogs of unobserved demand shocks (Supplementary Figure G5). Together, these findings support the assumption that changes in unobserved demand shocks are orthogonal to our instruments.

Perceived Product Quality Given estimates of $\{\alpha_p, \alpha_g, \rho\}$, we recover the mean utility term $\delta_{js}+\xi_{jst}$ by matching observed market shares using the standard BLP contraction mapping procedure (Berry et al., 1995). We then estimate the time-invariant component of perceived product quality $\hat{\delta}_{js}$ as the average of this term over time: $\hat{\delta}_{js} = \frac{1}{T}\sum_{t=2011}^{2013}(\delta_{js} + \xi_{jst})$.

Marginal Costs We recover marginal costs, mc_{jst}, that rationalize the observed prices under our Nash–Bertrand pricing assumption for each period t. We estimate marginal costs only for the pre-policy period ($t < 2014$), as the standard Nash–Bertrand first-order conditions no longer hold once the price ceilings are in place (Dubois and Lasio, 2018). We use only pre-policy marginal costs in our subsequent policy counterfactuals.

6.1.1 Results

Preference Parameters The top part of Table 1 reports our estimates of consumer preference parameters $\{\alpha_p, \alpha_g, \rho\}$. We find that consumers in poor health are less price sensitive than those in good health, although the differences are small in some therapeutic markets. Price sensitivity is the largest in the antacids market, consistent with the fact that antacids treat non-life-threatening symptoms, unlike the other conditions we study. Consumers substitute across molecules more frequently in the statins market ($\rho = 0.19$), while cross-molecule substitutions are less common in the ACE inhibitor, antacids, and CCB markets ($\rho \geq 0.50$).

Own-Price Elasticity & Markups We find that sales-weighted average own-price elasticities range from -1.49 to -2.35. The implied markups are substantial, with prices between 2.21 and 10.21 times marginal costs across markets.[37] Markups are the highest in the diabetes and CCB markets and lowest in the ACE inhibitor market. We also find significant within-molecule variation in markups, indicating that some brands command more market power than others.

Our marginal cost estimates are consistent with the accounting measures of production costs reported by Hill et al. (2018). Our estimates of elasticities and markups broadly align with prior findings in pharmaceutical markets (Chaudhuri et al., 2006; Dubois and Lasio, 2018), although we estimate higher markups for diabetes drugs.

[37] See Supplementary Figure G3 for the full distribution of marginal costs in each market.

Variation in Product Utility We find substantial variation in true utility between different brands of the same molecule, likely reflecting the lack of rigorous quality standards in India. This contrasts with the situation in high-income countries, where brand-level quality differences are believed to be minimal (Bronnenberg et al., 2015).

6.1.2 Robustness and Validation

Our demand estimates are robust to model misspecification in two key ways. First, under the exclusion restriction, our estimates capture the causal effect of prices on sales even if our demand model is misspecified (Andrews et al., 2025). Second, because our identification relies on policy-induced price variation rather than supply-side moments, our estimates of consumer preferences are robust to misspecification of our supply model and to potential correlation between demand and supply shocks.

We further evaluate the model's fit by assessing its ability to predict out-of-sample exit patterns, which are not used in estimation. As shown in Supplementary Table G5, the model correctly predicts 87% – 96% of observed exits across therapeutic markets. For products with a pre-policy market share above 5%, predictive accuracy improves to 93%–99%. Given the small number of exits in the data, most prediction errors reflect false positives. The model-predicted exit patterns also closely align with the corresponding event study results for these markets (Supplementary Figure B21).

In Supplementary Table G6, we report the sensitivity of parameter estimates to the moment conditions following Andrews et al. (2017). This analysis allows readers to assess how our estimates would change locally under potential violations of individual moment conditions.

6.2 Choice Frictions

Next, we turn to the estimation of consumer choice frictions (δ^{fr}). Our goal is to formally account for intrinsic differences in preferences between general consumers and expert physicians. In doing so, we isolate and quantify the residual variation in observed choice differences that is not explained by preference heterogeneity. This residual variation sheds light on the perceived quality gap, or choice frictions.

We assume that choice frictions only manifest in consumers' *brand choice* for a given molecule. To formalize this, we decompose the product utility δ_{js} into a molecule component and a brand-specific component: $\delta_{js} = \delta_{m(j)s} + \delta_{b(j)s}$. Here, $\delta_{m(j)s}$ represents the average utility of the molecule, defined as $\delta_{m(j)s} = \frac{1}{|j:m(j)=m|} \sum_{j:m(j)=m} \delta_{js}$, and $\delta_{b(j)s} \equiv \delta_{js} - \delta_{m(j)s}$ is the brand-specific deviation from that average.

We assume that consumers face choice frictions only in their brand choice, such that the brand utility can be decomposed as $\delta_{b(j)s} = \delta^{\text{true}}_{b(j)s} + \delta^{\text{fr}}_{b(j)s}$, while the molecule component matches the true utility: $\delta_{m(j)s} = \delta^{\text{true}}_{m(j)s}$. Although consumers may theoretically face frictions when choosing molecules, the evidence for such frictions is limited and inconclusive. Following Bernheim and Rangel (2005) and Bernheim (2024), we defer to consumers' revealed preferences when there is insufficient evidence of characterization failures. Differences in molecule choices between physicians and consumers may plausibly reflect welfare-relevant factors, such as differences in underlying health conditions and treatment match values. In contrast, a substantial literature has clearly demonstrated characterization failures in

consumers' choice of a brand for a given molecule (Bronnenberg et al., 2012).

We make two additional assumptions:

Assumption 6.1. *Physicians are informed about true brand utility* $\delta^{phy}_{b(j)} = \delta^{true}_{b(j)}$.

As discussed earlier, licensed and high-quality physicians have the best possible knowledge about product quality due to their medical training and clinical experience. By asking physicians to report brand-drug choices for their *own* use, we further minimize agency frictions that might otherwise distort prescribing behavior. The choice patterns remain stable when restricting the sample to the most knowledgeable physicians, reinforcing the interpretation that these choices reflect true product quality.

Assumption 6.2. *Physicians have the same utility specification as consumers:* $U^{phy}_{ij}(p, \delta, y_i, \alpha_i, \rho) = U_{ij}(p, \delta, y_i, \alpha_i, \rho)$.

This assumption imposes the same utility structure for physicians and consumers. Importantly, we do not assume identical model parameters; rather, we assume that individuals (consumers and physicians) with identical parameters would derive the same utility from a product. If our utility model was differentially misspecified between physicians and consumers, then this assumption would be violated. We defer a discussion of potential misspecifications and their implications to Section 6.2.1 on robustness and validation.

With these assumptions, we are ready to account for intrinsic differences in preferences and isolate the perceived quality gap that drives remaining differences in brand choices by general consumers and expert physicians. To make this precise, consider the difference in utility for product j between a consumer U_{ij} and a physician U^{phy}_{ij}:

$$U_{ij} - U^{\text{phy}}_{ij} = \underbrace{\delta_{m(j)} - \delta^{\text{phy}}_{m(j)}}_{\text{Molecule Preference}} + \underbrace{\delta_{b(j)} - \delta^{\text{phy}}_{b(j)}}_{\textbf{Choice Friction, } \delta^{\text{fr}}_{b(j)}} + \underbrace{\left(\alpha_i - \alpha^{\text{phy}}\right) p_j}_{\text{Price Sensitivity}} + \underbrace{\epsilon_{ij}\left(\rho\right) - \epsilon_{ij}\left(\rho^{\text{phy}}\right)}_{\text{Logit Shocks}}$$

To identify and isolate the brand-level choice friction term, $\delta^{\text{fr}}_{b(j)}$, we must adjust for the other differential factors—molecule preference, price sensitivity, and differential distribution of logit shocks governed by nesting parameter ρ.

Our estimation proceeds by first recovering the structural preference parameters for physicians, specifically $\{\alpha^{\text{phy}}, \rho^{\text{phy}}\}$. Recall that our survey includes two discrete choice experiments (DCEs): the choice following a random price increase for their current choice, and their choice when their current choice is removed from the choice set ("second choices"). These questions allow us to estimate $\{\alpha^{\text{phy}}, \rho^{\text{phy}}\}$ by maximizing the likelihood of the reported choices. Supplementary Section G.4 provides further details on the likelihood construction and the estimation procedure. After recovering $\{\alpha^{\text{phy}}, \rho^{\text{phy}}\}$, we estimate the mean utility component, δ^{phy}, by maximizing the likelihood of the physicians' survey choices.

With these parameter estimates for both general consumers (from market data) and expert physicians (from survey data), the residual systematic differences in brand choices identify choice frictions (δ^{fr}) — the wedge between true and perceived utility. Crucially, we eliminate any differences that arise

from preferences for different molecules, thereby isolating frictions to brand choices conditional on the molecule.

6.2.1 Robustness and Validation

We assess how potential issues associated with the estimation of choice frictions might influence our key results. As we later show in Section 7.1, accounting for choice frictions fundamentally changes the estimated welfare effects of the Indian policy. Therefore, it is important to rigorously assess potential biases and the robustness of these estimates.

Laboratory Drug Tests Our identification of choice frictions relies on the assumption that physicians' own brand choices reflect true product quality. If, instead, physicians had weaker preferences for quality, then the expensive brands favored by consumers would be of higher biochemical quality. To test this directly, we tested 62 samples of 61 brands regulated by the policy, covering 12 molecules across all five therapeutic markets. We selected brands to span the within-drug price distribution and oversampled brands with large differences between physician and consumer market shares, including both the multinational brands popular with consumers and the cheaper domestic brands chosen by physicians. A laboratory accredited by the National Accreditation Board for Testing and Calibration Laboratories (NABL) and certified under ISO standards conducted the tests.

The laboratory conducted two standard pharmacopeial tests. The *uniformity of content* test measures the amount of active ingredient in each tablet relative to the innovator brand. The *dissolution* test measures how much of the active ingredient is released into a solution that mimics the gastrointestinal tract, which determines whether the drug can be absorbed. Together, these tests capture the main dimensions along which low-quality drugs fail in practice: too little active ingredient, too much variation across tablets, or poor release. Supplementary Section C describes the sample, test protocols, pass criteria, and results in detail.

Biases from Discrete Choice Experiments In particular, one may be concerned about biases in our estimates of physician preferences derived from survey responses. The existing evidence on the credibility of discrete choice experiments is mixed. While recent studies show that discrete choice experiments yield estimates consistent with actual behavior in the job market (Mas and Pallais, 2017; Caldwell et al., 2025), others have demonstrated that respondents can systematically overstate price elasticities in such hypothetical surveys (Bernheim et al., 2022).

We assess this important concern in three ways. First, we confirm the internal consistency of the survey by showing in Supplementary Figure F3 that physicians' switching probabilities are largely monotonic in the size of the randomized price shocks. This finding shows that the survey captures relevant information about physicians' price elasticities.

Second, we perform a sensitivity analysis on key welfare estimates across a wide range of assumed physician price sensitivities: $\alpha^{\text{phy}} \in \left(0, 2 \times \hat{\alpha}^{\text{phy}}\right)$. The primary outcome examined is the gap between revealed-preference consumer surplus and friction-adjusted consumer surplus, which captures the magnitude of choice frictions. The full results, presented in Supplementary Figure G11, reveal two stark

patterns. First, the gap remains largely stable across this wide range of α values. Second, the friction-adjusted surplus usually increases as we make physicians more price elastic.

These patterns are intuitive: if physicians were more price elastic, their reluctance to choose expensive multinational brands would be primarily explained by the disutility from price rather than by low perceived quality. A greater role for price sensitivity would therefore imply a smaller magnitude for the unexplained residual, which constitutes the consumer choice friction. The existing literature suggests that respondents, if anything, tend to *overstate* price elasticity in discrete choice experiments (Bernheim et al., 2022). If, in truth, physicians are less price elastic than estimated, our current structural estimate would underestimate the size of consumer choice frictions and, consequently, understate the implied welfare loss from price controls. In this light, our estimates may be viewed as a conservative lower bound of the impact of choice frictions.

Finally, we consider an alternative true utility benchmark that does not involve the discrete choice experiments. In this specification, we impose that physicians have the same structural preference parameters as consumers, which were estimated using market data and policy variation. Under this assumption, we then recover an alternative measure of "true utility" that matches the physician's drug choices. Supplementary Figure G12 shows that the welfare results derived from this alternative specification are qualitatively similar to our baseline estimates. The friction-adjusted consumer surplus moves only marginally closer to the revealed-preference benchmark in some markets. This exercise underscores that the core conclusions are driven primarily by the stark differences in brand choices between consumers and physicians. Although we consider it important to account for intrinsic differences in preferences and characteristics, our main conclusions regarding the policy's welfare impact are robust to this refinement and a broad range of assumptions.

Unmodeled Heterogeneity Another potential threat to our identification strategy is the possibility that other welfare-relevant factors beyond income, price sensitivity, and molecule preferences influence brand choices and differ systematically between physicians and general consumers. To assess this concern, we implemented an additional consumer survey targeting various consumer groups who are similar to physicians in socioeconomic status but lack specific medical knowledge, including lawyers, government employees, and school teachers (Supplementary Section F.1.1). We implemented this survey in Bengaluru and Delhi—two large urban centers that are home to some of the best medical facilities in India. [38] We also surveyed 60 pharmacists.

We find that brand choices do not vary systematically with demographic factors such as sex, employment status, or industry, conditional on location and income (Supplementary Table F6). In contrast, more educated consumers and those who can correctly define a generic drug are less likely to buy expensive brands. Pharmacists, especially those with formal training and over one year of experience, are less likely to buy expensive brands (Supplementary Table F7). These findings further suggest that observed differences in brand choices are partly driven by information and knowledge, while unmodeled, non-knowledge-based preference heterogeneity plays a limited role.

[38] For budgetary and practical reasons, this survey was much simpler and shorter than the main physician survey. Eliciting information about complex medical products from non-medical professionals proved challenging because of their unfamiliarity with medical terms. Our surveyors verified responses based on prescriptions or product packaging. However, given this informational constraint, we were unable to include discrete choice experiments to directly estimate their preferences.

6.2.2 Results

Physician Preferences The middle panel of Table 1 reports estimated physician preference parameters, $\{\alpha^{\text{phy}}, \rho^{\text{phy}}\}$. In most cases, physicians are less price sensitive than the general consumer population and less willing to substitute across molecules in their own treatment choices. The finding of low price sensitivity suggests that the physicians' own drug choices are primarily driven by their assessment of product quality (δ^{phy}). This finding is consistent with our qualitative evidence that only a small fraction of physicians cite low prices as an important factor in their drug choices (Supplementary Figure F1).

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	-2.35	-2.29	-1.49	-1.59	-1.87
Avg Markup p/mc	2.21	3.00	10.21	5.55	4.75
Coef. of Var. p/mc	0.19	0.20	0.67	0.71	1.02
$cor(mc, \delta^{\text{true}})$	0.33	0.34	0.09	0.30	0.58
Coef. of Var. δ	3.67	6.78	0.51	0.50	0.75
Coef. of Var. δ^{true}	1.82	3.49	0.45	0.61	0.68

Notes: The table presents the demand parameters and summary statistics of model primitives. The top and middle panels present the estimated 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.

Choice Frictions We find that consumers systematically overvalue expensive multinational brands. Figure 7 shows the aggregate change in market shares across pre-policy price quartiles if consumers were to choose based on δ^{true} instead of δ. The figure shows overconsumption of high-priced brands, especially in the ACE inhibitor market. Consumers disproportionately overconsume products by multinational firms such as Sanofi and AstraZeneca.[39] These patterns have important welfare implications, as the Indian policy generated the largest price reductions for these expensive brands (Supplementary Figure G7).

The color of each point in Figure 7 shows the average active ingredient content of the tested brands in

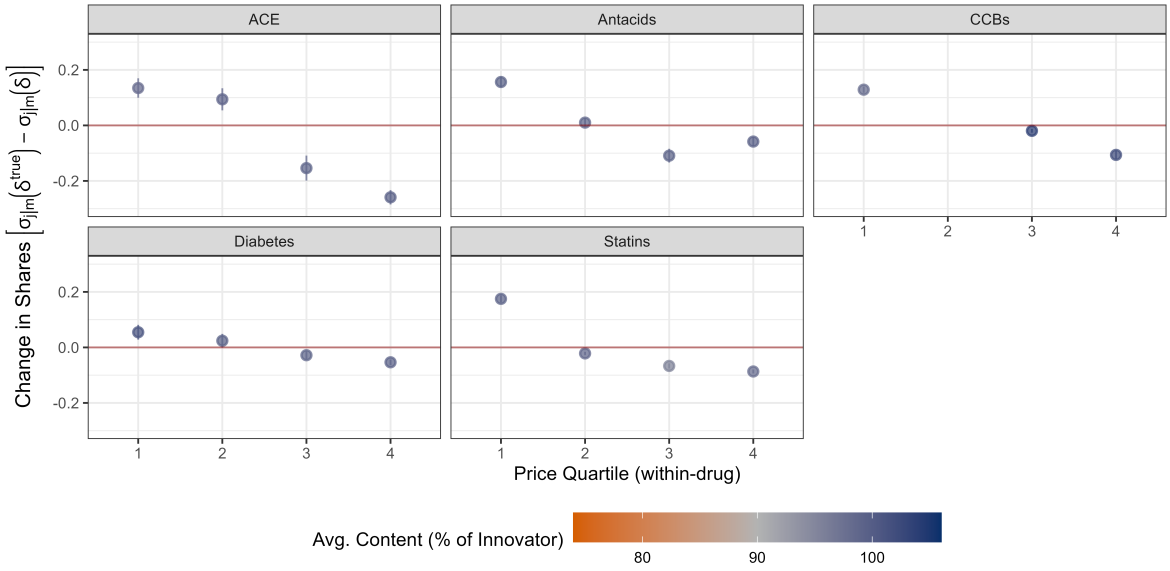
[39]See Supplementary Figure G4 and Supplementary Table G4 for the companies with the most and least bias.

that price quartile, measured in our laboratory tests. Measured content is close to the labeled strength across all price quartiles: brands that consumers overconsume relative to physicians contain the same amount of active ingredient as those they underconsume. For example, Sanofi's Cardace and FDC's Ziram, two brands of ramipril at opposite ends of the price distribution, contain 98.7% and 97.7% of their labeled strength, respectively, and both release 87% of their active ingredient in the dissolution test against a pharmacopeial requirement of 70%. These results support our interpretation that consumers' preference for expensive brands reflects choice frictions rather than differences in biochemical quality.

Costs and True Quality We also find that the variation in *perceived* utility exceeds that in *true* utility in most therapeutic markets. This result suggests that choice frictions have generated spurious product differentiation and, consequently, exacerbated market power beyond the level warranted by true quality differences.

Finally, we document a positive correlation between marginal costs and true product quality across all five therapeutic markets. This finding suggests that stringent price controls could potentially lead to the exit of high-quality products and generate significant negative welfare consequences.

Figure 7: Price Differences, Choice Wedges, and Measured Drug Quality



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 quartiles based on within-drug prices from the AIOCD. Each point represents the mean choice wedge for a given quartile; only drug–quartile cells with at least one tested brand are shown. The color of each point shows the average active ingredient content (uniformity of content test, percent of labeled strength) of the tested brands in that cell. See Supplementary Section C for details on the sample and tests.

7 Policy Analysis

With the model parameters estimated, we quantify the welfare effects of the Indian policy and evaluate alternative policy interventions. Variation across therapeutic markets provides a useful testbed for assessing policy performance under different market conditions.

In each counterfactual scenario, we compute an equilibrium by iterating over firms' best responses until convergence.[40] At the resulting equilibrium, we then calculate consumer surplus, firm profits, and total welfare, both with and without adjusting for choice frictions in calculating consumer surplus. All outcomes are reported as changes relative to the pre-policy market equilibrium in 2013, aggregated across states.

Unless otherwise noted, units are expressed in dollars per person per year, assuming that a consumer takes one standard dose (i.e., one DDD) daily over the course of a year. We use this per-capita measure to simplify exposition. Given market sizes ranging from 5 million to 30 million consumers, the aggregate welfare effects are economically significant.

7.1 Welfare Effects of the Indian Policy

Figure 8 summarizes the effects of the Indian policy on drug prices, consumption, and welfare. On average, prices fell by between 18% and 29%, consistent with our event study estimates in Section 4. The price reductions were largest in therapeutic markets with greater pre-policy price dispersion, such as the statins market.

The price ceilings increased drug consumption without triggering many product exits. The increase in consumption is particularly pronounced in the ACE inhibitor and statins markets, where price reductions were larger and consumers more price sensitive. Notably, the policy increased the total consumption of regulated, essential drugs by between 3% and 10%. Overall, the Indian policy accomplished its central objective of improving access to essential medicines.[41] Although the policy reduced firms' profits by \$0.90 to \$5.09 per capita, most firms remained in the market, and product exits were uncommon.

Under revealed preference, consumer surplus increases by between \$0.74 and \$4.93 per capita. These gains arise through two channels. First, price-insensitive consumers who have been buying expensive brands now pay less because of lower prices. In our model, these consumers tend to be sicker and wealthier (Supplementary Figure G6). This change represents a transfer from firms to consumers. Second, lower prices induce substitution toward the now-cheaper brands, generating efficiency gains by correcting monopoly distortion. To contextualize the magnitude of these effects, the average consumer spent \$54.90 on statins in 2013, which constituted 9% of the median household's annual consumption budget. The \$4.93 consumer surplus gain in this market thus amounts to 9% of expenditures on statins, or roughly 1% of the median household consumption budget. Across therapeutic markets, the increase in consumer surplus ranges from 3% to 17% of annual treatment costs. Total welfare gains are larger for sicker patients with multiple diseases.

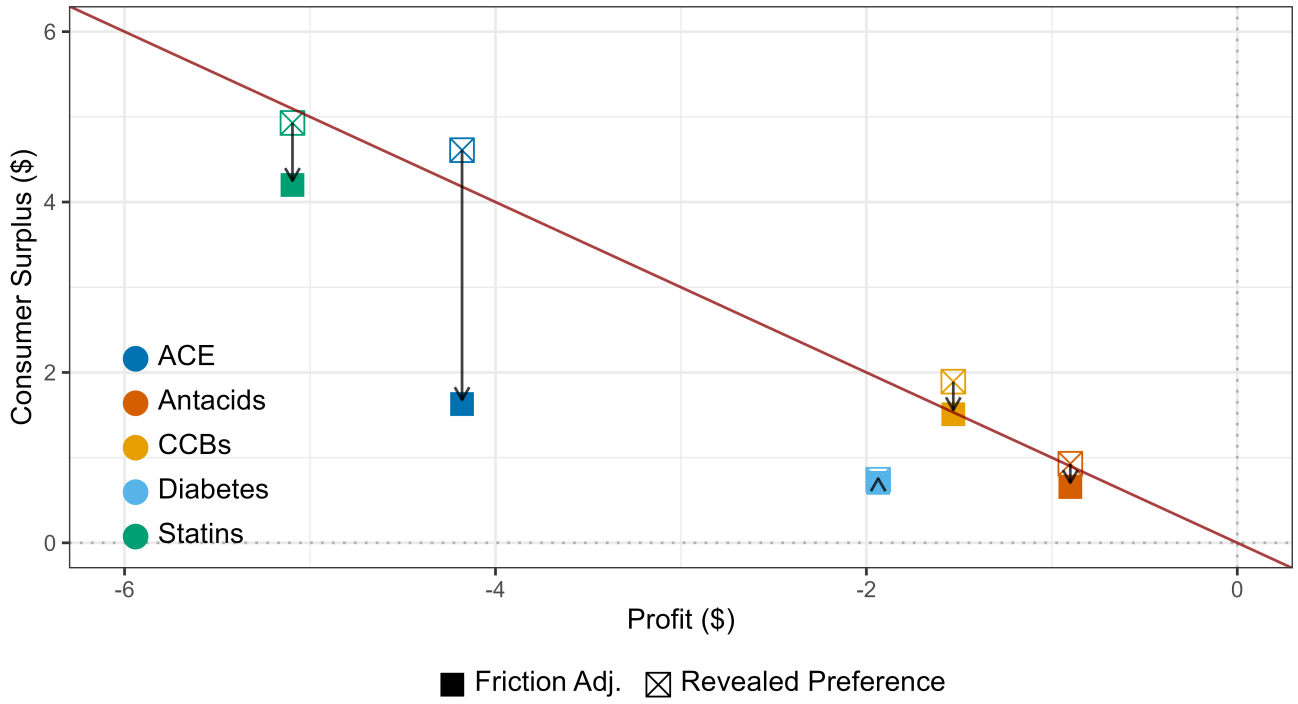
Changes in total social welfare range from −\$1.20 to \$0.43 per consumer. These net effects reflect two opposing forces: welfare gains from reduced monopoly distortion and welfare losses from product exits. The gains outweigh the losses in most markets. A notable exception is the diabetes market, where the exit of a product with particularly high perceived utility led to a large welfare decline.

After incorporating choice frictions, true gains in consumer surplus range from \$0.66 to \$4.20 per capita. These gains are 6% to 65% smaller than those implied by revealed preference, as the Indian

[40] See Supplementary Section G.5 for details on our computational algorithm and our tests for multiple equilibria.

[41] While our welfare measures partially capture the benefits from this increased consumption, they may understate the full benefits. First, consumers may undervalue preventive treatments such as statins. Second, we do not account for public health externalities. We plan to study the impact on public health in future work.

Figure 8: Welfare Impacts of the Indian Policy Under Different Normative Benchmarks



	ACE	Antacids	CCBs	Diabetes	Statins
Positive Outcomes					
Prices (%)	-0.23	-0.21	-0.18	-0.22	-0.29
Share Regulated (p.p)	0.10	0.03	0.04	0.03	0.09
Share Inside (p.p)	0.04	0.02	0.03	0.01	0.05
Share Exit (%)	0.07	0.06	0.02	0.05	0.06
Normative Outcomes					
Profit ($)	-4.18	-0.90	-1.53	-1.94	-5.09
Revealed C.S. ($)	4.61	0.93	1.89	0.74	4.93
Revealed Welfare ($)	0.43	0.03	0.36	-1.20	-0.17
True C.S. ($)	1.63	0.66	1.51	0.70	4.20
True Welfare ($)	-2.55	-0.25	-0.02	-1.23	-0.89

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

policy disproportionately steered consumers toward overvalued products. Once firm profits are included, true social welfare declines in all five therapeutic markets.

To illustrate the intuition behind the results, we revisit the example of ramipril. Cardace—the most expensive and popular brand of ramipril—was significantly overvalued by consumers. The policy lowered Cardace's prices by 40%, drawing in 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. As a result, marginal consumers who switched ended up paying more for a product of similar quality, generating a welfare loss despite the policy-induced price reduction.

These results highlight an important interaction between market power and choice frictions. In the absence of choice frictions, price ceilings that do not induce product exit help correct monopoly distortions and improve social welfare. However, when both market failures are present, high markups act as a *de facto* "corrective tax" that discourages consumers from overconsuming overvalued products. By attempting to correct market power, price controls inadvertently offset this corrective force and exacerbate inefficiencies caused by choice frictions, ultimately reducing overall welfare.

7.2 Choosing Price Ceilings

Our main results in Section 7.1 reveal two key shortcomings of the Indian policy. First, it was poorly targeted: it generated the largest price reductions for precisely those products that consumers systematically overvalue due to choice frictions. Second, the policy lacked flexibility, imposing a uniform price ceiling across all brands of a given drug. While exit was limited under the observed policy, further tightening of the uniform price ceiling risks triggering exits of high-quality, high-cost products. Given these structural inefficiencies, we explore the scope for alternative designs of price ceilings to improve aggregate welfare.

Price control is not a binary policy: importantly, regulators must choose the level of the price ceiling. We explore how regulators can set price ceilings more effectively. Following the structure of the Indian policy, we first evaluate drug-level price caps ranging from the lowest to the highest pre-policy brand prices. The results are presented in Figure 9.

When regulators impose very low ceilings, prices fall substantially, but many high-utility brands exit the market. In such cases, the welfare losses from product exit usually outweigh the benefits of lower prices, reducing consumer surplus in most markets. Interestingly, the decline in true consumer surplus is usually smaller than the decline based on revealed preference consumer surplus, since some products that exit are overvalued. Higher price ceilings near the pre-policy price of the median brand strike a better balance between reducing markups and preventing exit. At these levels, both perceived and true consumer surplus usually increase.

The optimal price ceiling to maximize consumer surplus varies across therapeutic markets, reflecting differences in pre-policy markups. In the CCB market, where markups are high, ceilings set as low as the 20^{th} percentile of the pre-policy price distributions do not lead to exit and benefit consumers. In contrast, in the antacids and statins markets, where markups are lower, such aggressive price ceilings trigger welfare-reducing exits, and the optimal ceilings are much higher. These results highlight that even within the same industry in the same country, optimal price regulation should account for the underlying market structure and competitive landscape in each individual market.

As with the Indian policy, we find that the consumer surplus gains from drug-level price ceilings are typically smaller than those implied by revealed preference, and that true social welfare generally declines. By design, *any* drug-level price ceiling imposes larger price cuts on higher-priced products—precisely those that consumers tend to overvalue. As a result, such policies exacerbate the overconsumption of overvalued products, making it difficult to achieve meaningful improvement in allocative efficiency.

A potential solution is to set more granular price ceilings at the *brand* level. This approach resembles the cost-based price caps implemented on a much smaller scale in India in 1995.[42] Political constraints aside, the efficacy of such policies depends on the availability of information about costs, quality, and markups. Regulators do not need perfect information—effective interventions are possible using only coarse information on economic primitives. For example, if regulators can identify an upper bound on marginal costs and distinguish overvalued products (e.g., multinational brands), setting price ceilings at the cost bound for weakly undervalued brands can robustly improve welfare. We demonstrate this theoretically (Supplementary Section G.8) and empirically (Supplementary Table G10).[43] An alternative or complementary approach is to reduce choice frictions, which we discuss next.

7.3 Reducing Choice Frictions

Instead of regulating market prices, policymakers may seek to reduce choice frictions directly. Insofar as correcting choice frictions reduces perceived product differentiation, such a policy would also reduce market power. We evaluate an idealistic case where all choice frictions are eliminated, allowing consumers to make choices based on true utility δ^{true}. Results are shown in Figure 10.[44]

In our first counterfactual, consumers make choices based on δ^{true} while prices remain fixed. As expected, this intervention improves consumer surplus, as some consumers switch from expensive, overvalued brands to cheaper, undervalued ones. The gains are especially large in markets with substantial choice frictions: \$11.0 in the ACE inhibitor market and \$5.10 in the diabetes market (Supplementary Table G7). The intervention also redistributes profits from overvalued to undervalued firms and slightly reduces total industry 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. 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 G8).

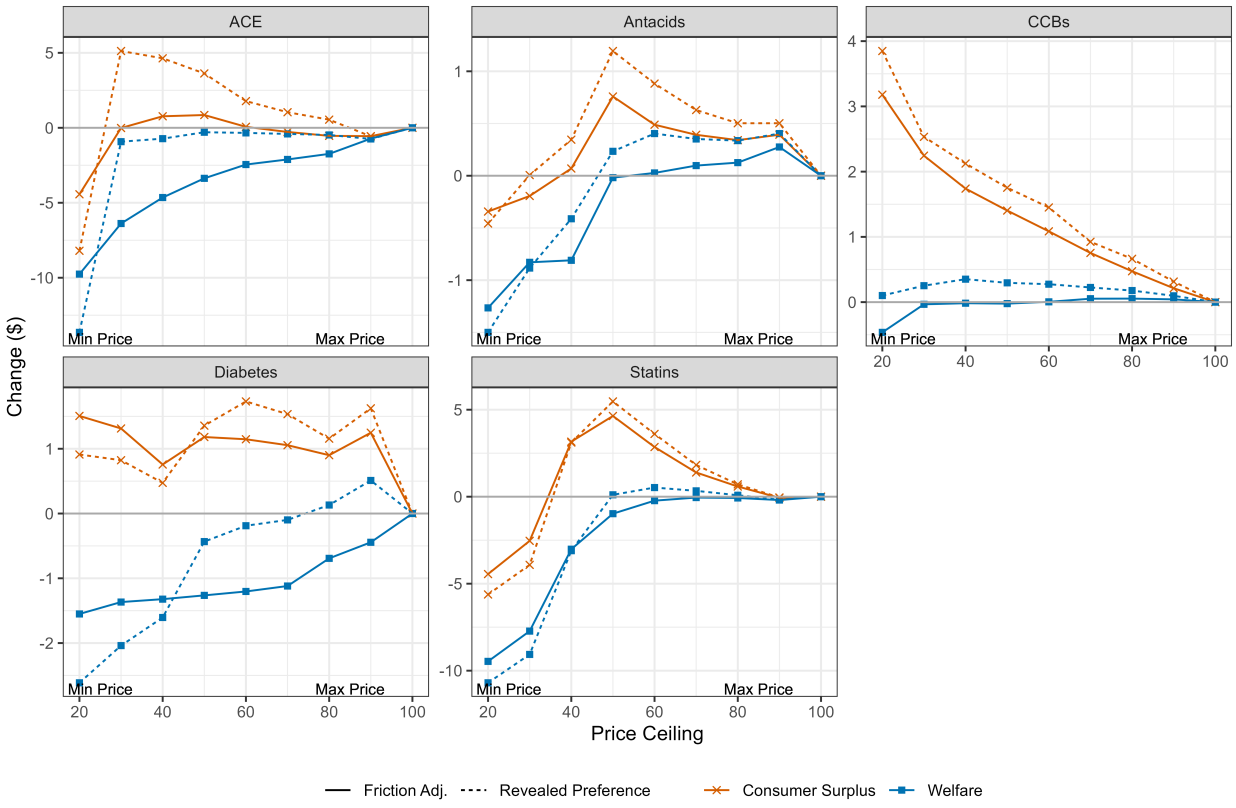
A key limitation of removing choice frictions alone is that it does not address market power arising from true quality differences. The welfare gains from this intervention depend on the relative impor-

[42] In 1995, price ceilings were set to a fixed markup over distribution costs, outward freight, manufacturer margins, promotional expenses, and trade commissions, as determined by Indian regulators.

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

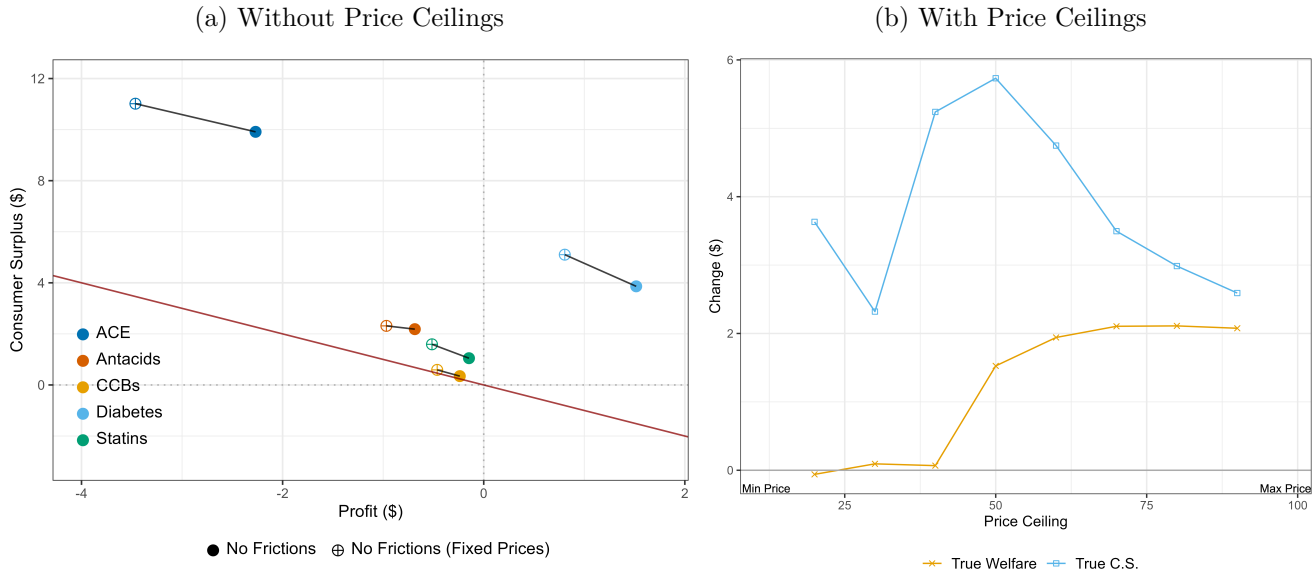
[44] In practice, eliminating choice frictions is challenging for at least two reasons. First, effective policy design requires a clear understanding of the underlying mechanism. If frictions stem from limited consumer information, awareness campaigns may be appropriate; if agency problems are the primary concern, reforms should target the financial incentives facing physicians. Our physician survey suggests that both mechanisms play some role (Supplementary Figures F4 and F5). Second, designing effective policies is difficult, 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: Welfare Changes 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.

Figure 10: 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.

tance of the two market failures. In the ACE inhibitor market, where choice frictions are pronounced, eliminating these frictions achieves 78% of the first-best welfare gains (Supplementary Figure G9).[45] In contrast, the gains are minimal in the CCBs market, where market power driven by true quality differences is the primary market failure.

Combining friction reduction with price controls could generate substantial welfare gains. Figure 10b presents the welfare impacts of various levels of price ceilings after choice frictions have been eliminated, aggregated across five therapeutic markets. Results by individual markets are shown in Supplementary Figure G10. We find that removing choice frictions in tandem with price controls significantly increases both consumer surplus and social welfare, up to the point where they trigger product exits. These results underscore the promise of policies that address both market failures.

7.4 A Broader Set of Policies

We briefly discuss three additional policies commonly implemented in other countries to improve access to high-quality essential medicines: government entry, generic substitution, and quality standards. Since India has not implemented these policies, we must make important assumptions about their design and certain economic primitives (e.g., the fixed cost of introducing a government brand). Based on these assumptions, we simulate the impact of each policy using our structural model. Given the speculative nature of these assumptions and the model-based extrapolation, these results should be viewed as exploratory evidence on important policy questions that warrant more rigorous analysis in future research.

[45] Supplementary Table G9 reports the share of first-best surplus gains achieved under all policy scenarios.

Government Entry Under this policy, the regulator introduces a high-quality government brand sold at marginal cost. Consumers undervalue the public option to the same extent as the average Indian-manufactured brand. Despite choice frictions, price-sensitive consumers switch to this low-cost, high-quality alternative. The increased competition also drives down private-sector prices, benefiting all consumers. Overall, the policy improves both consumer surplus and total welfare, before accounting for the fixed cost of launching the public option. (See Supplementary Section G.9 for details.)

Mandatory Generic Substitution A generic substitution policy requires consumers to purchase the cheapest brand of each drug, effectively imposing *undifferentiated* Bertrand competition among firms selling the same molecule. In equilibrium, the lowest-cost product remains in the market and sets a price equal to the second-lowest marginal cost. In our setting, where marginal costs are positively correlated with true quality, the remaining products tend to be of low quality. As a result, while prices fall, the loss from losing high-quality brands outweighs the gains from lower prices. Consumer surplus, firm profits, and overall welfare all decline under this policy. This result highlights the limit of generic substitution laws in the absence of rigorous quality standards. (See Supplementary Section G.10 for details.)

Quality Standard Under a minimum quality standard, substandard brands must either exit the market or invest in quality upgrades. If these brands exit, the market would be left with a smaller set of expensive, high-quality brands, and the loss of low-cost options would reduce both consumer surplus and total welfare. In contrast, if substandard brands can improve quality at relatively low cost, the market would have more medium- to high-quality products. In this scenario, consumer surplus, profits, and total welfare all increase, albeit alongside higher drug prices. We also show that combining quality standards with mandatory generic substitutions, which jointly address both market failures, could deliver further welfare gains in some markets. (See Supplementary Section G.11 for details.)

8 Conclusion

In this paper, we study the role of two common market failures — market power and choice frictions — in shaping the welfare effects of a large-scale pharmaceutical price control policy in India. We document three key empirical findings. First, the policy led to large price reductions for expensive branded drugs and higher sales for these products. Second, despite large price cuts, supply-side disruptions were minimal, and total drug utilization increased. Finally, some consumers choose expensive brands over cheaper alternatives of similar quality because of choice frictions.

We combine these empirical patterns with our model to assess the Indian policy and alternative policies. Under revealed preference, lower prices increase consumer surplus and social welfare by correcting monopoly distortions. However, the true consumer surplus gains are smaller and true social welfare declines, because consumers systematically overvalue the expensive brands that experience the largest sales increase. Policies that jointly target both market failures have the potential to deliver significant welfare improvement.

Price controls are widely used in pharmaceutical markets and many other sectors, including housing, utilities, and food staples. These policies are particularly common in developing countries, where

consumers face substantial frictions in evaluating product quality. Our study highlights that beyond the well-documented concerns about shortages and investment incentives, choice frictions may also play a critical role in shaping the welfare effects of price regulation. While we focus on the Indian pharmaceutical market, our framework provides a generalizable empirical approach for recovering key economic primitives central to evaluating price control policies across a range of settings. More broadly, our framework is also useful for evaluating policies in settings where choice frictions interact with other market failures, such as subsidy designs in electric vehicle markets that involve both environmental externalities and consumer choice frictions.

Several important questions related to price controls, especially in pharmaceutical markets, remain open for future research. First, the effects of price controls on health outcomes are not yet well understood. Second, understanding the effects of price controls on how consumers learn about new brands and molecules is important for a more comprehensive welfare assessment. Third, as pharmaceutical markets become increasingly global, price regulations in one country can influence supply and pricing elsewhere. Exploring the international spillovers and policy trade-offs in a global market, with complementary or competing interests between countries, is an important direction for future research.

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