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, 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 non-price 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).

In response to concerns about drug affordability, policymakers often impose price controls that cap the prices firms can charge consumers (Kyle, 2025). The welfare effects of price controls are ambiguous when firms have market power or consumers face choice frictions, such as misperceptions about product quality. A well-established literature predicts that, in competitive markets, price controls lead to undersupply and efficiency losses (e.g., Arrow, 1951; Glaeser and Luttmer, 2003). By contrast, when pharmaceutical companies exercise market power, price controls can lower prices without disrupting supply, thereby improving access to drugs. In standard welfare analysis that assumes fully informed, optimizing consumers, greater access increases welfare. However, in healthcare markets, consumers often hold mistaken beliefs about the benefits of drug products (Arrow, 1963). In such settings, welfare assessments based solely on revealed preference can be misleading—an issue previously unexplored in discussions of price controls. For example, a consumer who purchases a drug after a price cut could be worse off if she overvalues the drug and would have been better off without it.

In this paper, we provide a novel empirical analysis on the role of market power and choice frictions in shaping the welfare impacts of a large-scale pharmaceutical price control policy in India. Using comprehensive market data and a natural experiment, we estimate the causal effect of the Indian policy on prices, sales, and product availability. In addition, we collect novel survey data 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. However, 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, in the spirit of Bronnenberg et al. (2015), to measure the true utility of different brands. We conducted a novel survey of 617 licensed physicians, recording the brands they use for their *own* treatment. In healthcare, physicians are likely the group of consumers with the best possible information. We specifically selected only licensed physicians who are well informed as measured by a number of metrics. Furthermore, the physicians' choices are not distorted by agency issues because we ask them about their choices for themselves. For these reasons, we interpret the choices of these experts as reflecting their true utility, *ceteris paribus*.

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 that have FDA approvals 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.

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

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

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 of 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 mitigates their overconsumption. 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 poli-

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

cies 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 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. We also evaluate other commonly used nonprice regulations, such as government entry, generic substitution, and quality standards.

Our paper primarily contributes to three strands of literature. First, we advance the literature on the economics of price controls. A large body of research has shown, from both theory and practice, that price controls are harmful in competitive markets because they reduce the supply of high-quality products (Olsen, 1972; Raymon, 1983; Deacon and Sonstelie, 1991; Glaeser and Luttmer, 2003; Davis and Kilian, 2011; Diamond et al., 2019). Research on price controls in the presence of market failures is more sparse, comprising a small set of theoretical studies (Salop and Stiglitz, 1977; Yohe, 1978; Smith and Williams, 1981) and an even smaller set of empirical papers on two market failures: market power (Cuesta and Sepúlveda, 2021) and spillovers in rent control (Sims, 2007; Autor et al., 2014). Our primary contribution is to empirically analyze price controls in the presence of both market power and choice frictions. We show that the interaction between these two market failures is crucial for understanding the impact of price controls on market outcomes and welfare in an important real-world setting. Our results also add to a broader empirical literature on public policy with multiple market failures (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).

A few recent studies have examined the Indian price control policy, including prospective analyses of potential product exits (Mohapatra and Chatterjee, 2015) and reduced-form evaluations of its short-term market impacts (Jaikumar et al., 2023; Dean, 2025). Our study analyzes a broader set of market outcomes over a longer time horizon and incorporates empirical estimates of choice frictions into an equilibrium model. We provide the first formal welfare analysis of the Indian policy and evaluations of alternative policies.

Second, our paper contributes to the literature on welfare analysis with choice frictions, partic-

ularly in pharmaceutical markets.[3] While many studies on pharmaceutical regulation acknowledge the potential for such frictions, they often abstract from them or provide wide welfare bounds under different assumptions (Song and Barthold, 2018; Carrera and Villas-Boas, 2023; Kortelainen et al., 2023; Atal et al., 2024; Cao et al., 2024). We develop a novel approach to directly measure choice frictions and incorporate them in policy analysis for pharmaceutical markets. Our analysis builds on the broader literature on brand preferences, which has focused largely on high-income countries (e.g., Bronnenberg et al., 2015), and sheds light on the distinct nature of brand preferences in LMICs, where quality regulation is often weaker. Our approach also complements other methods in the existing literature that leverage laboratory tests (Bate et al., 2011; Bennett and Yin, 2019) or government inspection reports (Dean, 2025; Ishitani, 2025) to measure drug quality.

Finally, we provide a comparative analysis of a broad set of pharmaceutical regulations studied in the literature (e.g., Dubois and Lasio, 2018; Maini and Pammolli, 2020; Atal et al., 2022; Dubois et al., 2022; Atal et al., 2024; Barwick et al., 2025). Leveraging our quasi-experimental setting, we provide causal evidence on the effects of price controls and credibly estimate key primitives for several major therapeutic markets. Our model then allows for a systematic counterfactual evaluation of alternative policies, including information intervention, government entry, mandatory generic substitution, and quality controls.

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).[4] 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 brands of the drug Ramipril-5mg, sold by the manufacturers Sanofi and FDC, respectively.

India is home to over 1,000 pharmaceutical manufacturers. Broadly, these firms can be classified

[3] See Handel and Kolstad (2015); Baicker et al. (2015) for analogous studies in insurance markets.
[4] ATC-4 groups are commonly used by researchers and policymakers to define markets.

into three groups: multinational companies, Indian national companies, 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 these companies also sell at least one molecule in the US. Indian national companies produce an average of 56 molecules and also operate nationwide. A third of them export to the US. In contrast, regional firms sell, on average, six molecules in five Indian states, do not export to the US, and generate significantly 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.[5] 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.[6] Despite these regulations, 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.

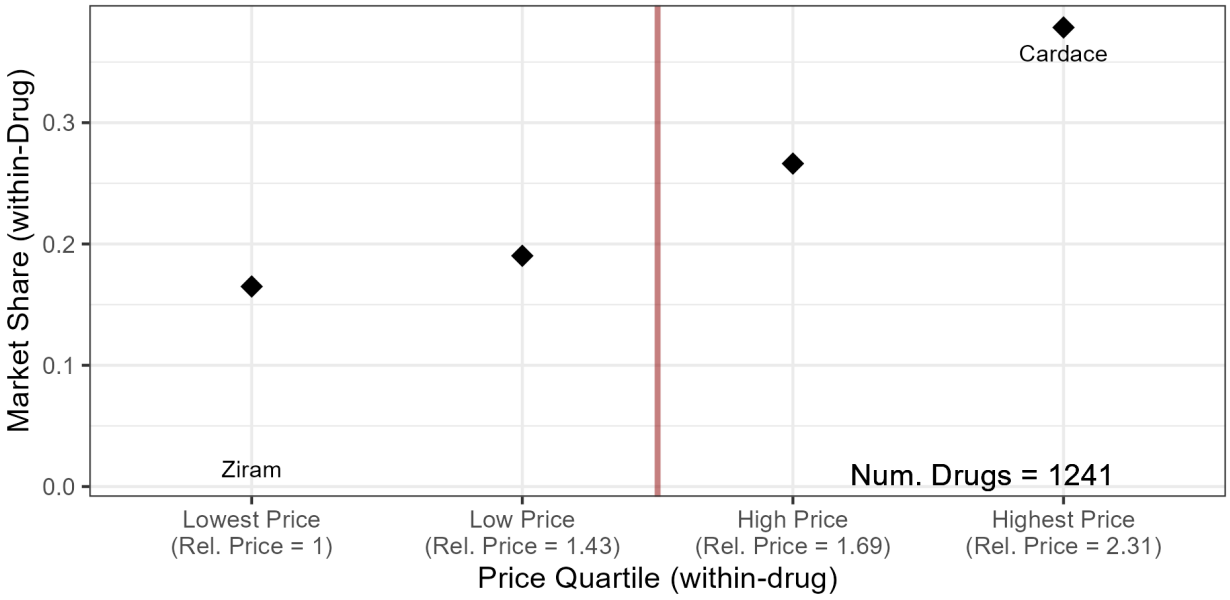
Brand preferences may reflect actual differences in product quality, which is not reliably screened due to weak regulation. Quality can vary between brands due to differences in input quality, manufacturing practices, or transportation and storage conditions. Before 2017, licenses to manufacture a new brand of an existing drug were granted based on visual inspections rather than clinical bioequivalence tests, which have been standard in the US and Europe since at least the 1990s.[7] Furthermore, there are widespread concerns about the reliability of government inspections.

[5] 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).

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

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

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.

A recent policy episode prominently highlights these quality concerns in India.[8] In August 2023, regulators proposed a policy that would require physicians to prescribe 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.

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

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

needs of the Indian population.[9] 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 constitute 90% of regulated drugs, the price ceiling was the unweighted average price of all brands with 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 they were updated annually by the government to account for inflation.

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.[10] 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 it, only 95 drugs were subject to price controls under a 1995 law. After India began enforcing pharmaceutical patents in 2005 (Sampat and Shadlen, 2015), concerns about rising drug prices led to years of deliberation on price control policies. Although 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.[11] The AIOCD data are ideal for studying the Indian policy since regulators set price ceilings based on information in this data.

The AIOCD collects data from a panel of 12,000 stockists—intermediaries between pharmaceutical companies and private retail pharmacies—covering nearly the entire universe of drug sales in private pharmacies in India.[12] We observe sales and prices at the level of a stock-keeping unit (SKU), which is a combination of brand, molecule, dosage, and package size. We convert all

[9] 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.

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

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

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

variables to per-pill units and aggregate them to the brand–molecule–dose level.

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.[13] We discuss additional details on the sample construction process in Supplementary Appendix A.1.

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 Pharma Intelligence provides timelines for drug development and drug launches. See Supplementary Section A.2 for additional information on these data sources.

3 Model

In this section, we introduce our framework for analyzing price controls. We begin with a high-level overview, 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.

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

Beyond pricing, price controls can also influence market participation. A sufficiently low price ceiling induces product exits, 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,[14] as specified by the following random coefficient nested logit model (Berry et al., 1995):

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

The term δ_{js} represents the mean time-invariant utility that 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 shocks, which consist of two components: a molecule-level shock $\zeta_{im(j)st}$ and a product-level shock ϵ_{ijst}. We assume that ϵ_{ijst} is i.i.d. type-1 extreme value and $\zeta_{im(j)st}$ is distributed such that $\zeta_{im(j)st} + (1-\rho)\,\epsilon_{ijst}$ is also i.i.d. type-1 extreme value, yielding the nested logit model (Cardell, 1997; Berry, 1994). The molecule-level shocks capture heterogeneous match effects with different treatments. For example, patients may have different preferences for a particular molecule because of differences in comorbidities. The product-level shocks capture idiosyncratic factors such as availability in a consumer's local pharmacy. The parameter $\rho \in [0, 1]$ captures the importance of the molecule-level shock relative to the product-level shock and thus governs the substitutability across molecules. A higher ρ implies that consumers are less likely to switch across molecules.

Consumers trade off the utility of a product with its price p_{jst}, depending on their price sensitivity α_i. The distribution of price sensitivity is denoted by $H_s(\alpha_i)$.[15] Under this setup, the market share of a given product σ_{jst} is

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

[15] 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 C.2 for an illustration.

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

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 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 C.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.[16]

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

[16] Our model also assumes that choice frictions do not vary between consumers. Extending the model to allow for heterogeneity in choice frictions as random effects does not influence aggregate market-level welfare but does alter the distribution of welfare. We focus on market-level outcomes in our analysis and defer research on distributional impacts to future work. In Supplementary Section F.7, we show the sensitivity of our results to different assumptions about the correlation between price sensitivity and choice frictions.

$I_{ist}(\delta, p) - \sigma_{ist}\delta^{\text{fr}}$, 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.

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

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

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

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

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:

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

Note that prices change because of two forces. First, the price 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.[17] The firm chooses a subset of these products $J_f \in P(\mathcal{J}_f)$ to supply in the market by removing the products in $\mathcal{J}_f \setminus J_f$, where $P(\mathcal{J}_f)$ denotes the power set of $\mathcal{J}_f$.

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

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

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

Firms make product exit decisions simultaneously with complete information about their rivals' 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 F.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

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

remained unchanged following price controls. Similarly, we do not model the effect of price controls on the launch of new molecules, given the limited changes we find in Section 4.5.

We also treat product quality δ_j^{true} and marginal costs mc_j as exogenous. 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 can jeopardize profits from these lucrative export markets. Furthermore, domestic regulatory enforcement has strengthened in recent years: a bioequivalence standard was introduced in 2017, inspections of manufacturing facilities have become more frequent, and licenses for substandard manufacturers have recently been revoked (Government of India, 2017). Our survey evidence further supports this assumption: over than 75% of the physicians in our survey report no change in their perception of product quality following the price control policy (Supplementary Figure E2).

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.

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.

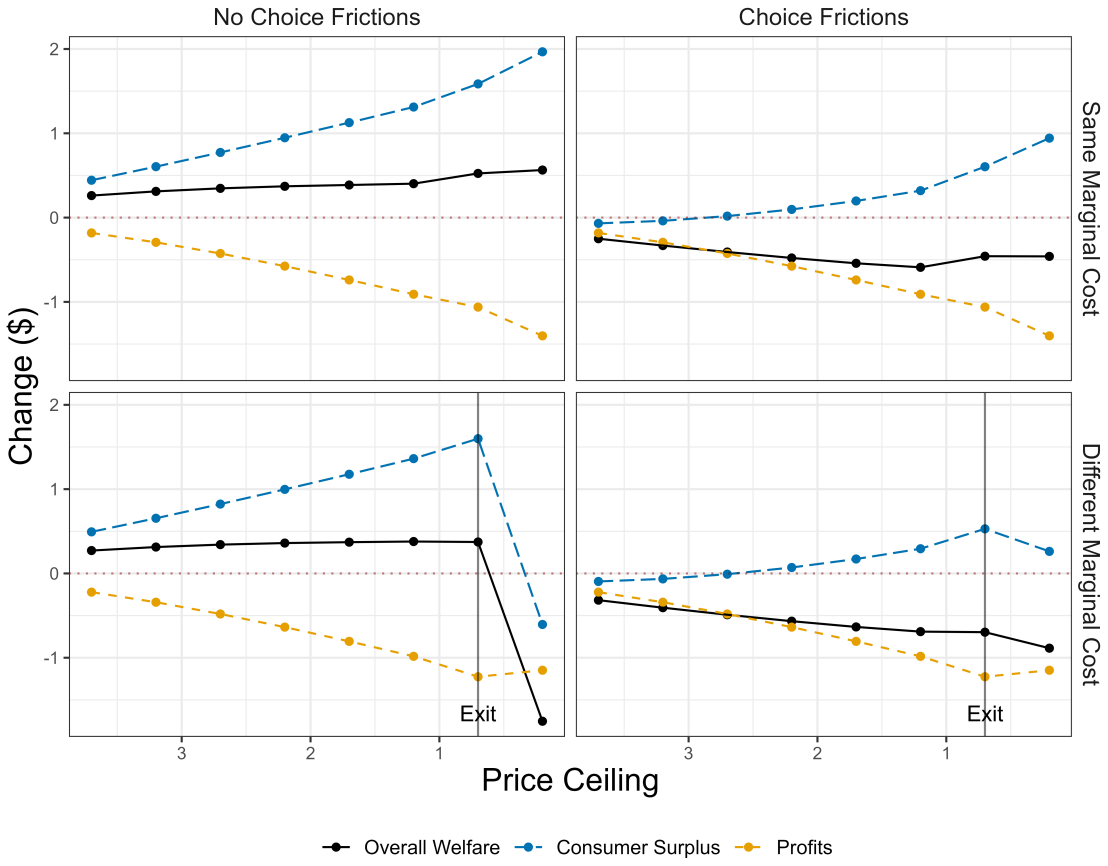
We illustrate the effect of a price ceiling $0 < \overline{p} < p_h^{\text{eq}}$ under four scenarios that vary in marginal cost mc_h and choice friction δ_h^{fr}. In the first case, brand h has higher true utility, and all brands have the same marginal cost ($\delta_h^{\text{fr}} = 0, mc_h = 0$). In 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.[18]

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

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.

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 take in Section 6.

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 the 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 have responded 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 prepolicy prices represented a significant departure from 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 B12, 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

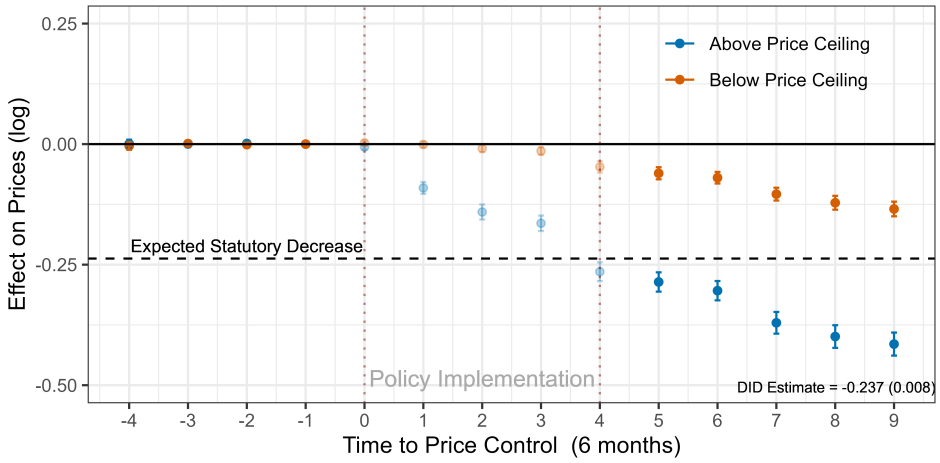
In Figure 3a, we present our estimates of the effect of the Indian policy on (log) prices. There are no statistically significant or economically meaningful pretrends in prices, validating our parallel trends assumption.[19] After the policy was phased in, prices of regulated products above the ceiling 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.

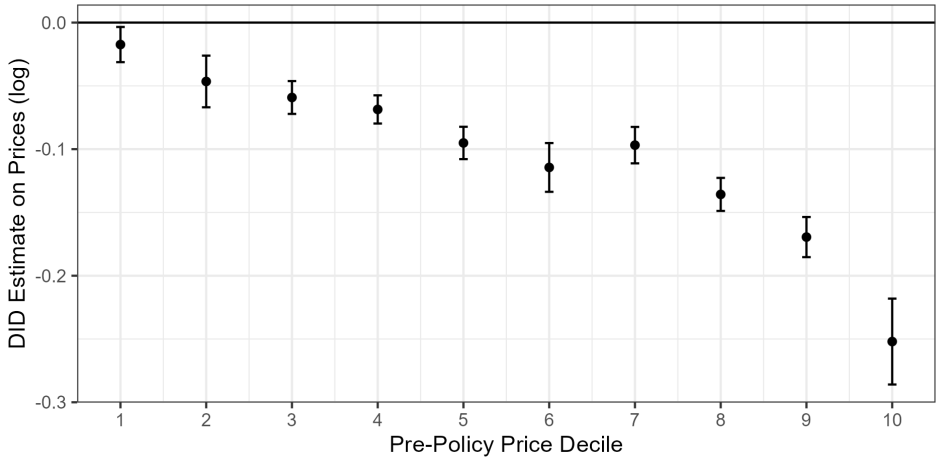
Figure 4a shows that sales of regulated products above the price ceiling increased by 36%

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

Figure 3: Effect of the Indian Policy on Prices



(a) Event Study Estimates



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

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

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. If the pretrend had continued post-policy, our estimates would be downward biased. In Supplementary Figure B13, 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 medications, 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) in response to the price changes documented above (see also Supplementary Figure B14). 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 B15). These results show that price controls led to substitution across therapeutic options and expanded access to essential medicines.

4.4 Results: Exit, Entry, and Detailing

To evaluate changes in product availability, we estimate the effects of the Indian policy on the number of brands per drug. We find that the policy 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 B16), while we observe no significant change in new brand entry (Supplementary Figure B17). While the overall impact on product availability is negligible, we do observe policy-induced product exits in 17.8% of therapeutic markets (Supplementary Figure B18), where they could have significant welfare implications.

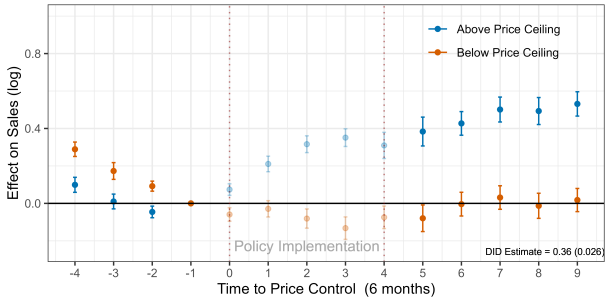
We also estimate the impact of the Indian policy on advertising to physicians ("detailing"), similar to contemporaneous research in the U.S. context (Hristakeva et al., 2024). We use the IQVIA ChannelDynamics dataset, a leading resource of market intelligence that records monthly detailing expenditures at the firm–molecule–channel level in India.[20]

We find no significant change in detailing on the extensive margin (Supplementary Figure B19). 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.[21]

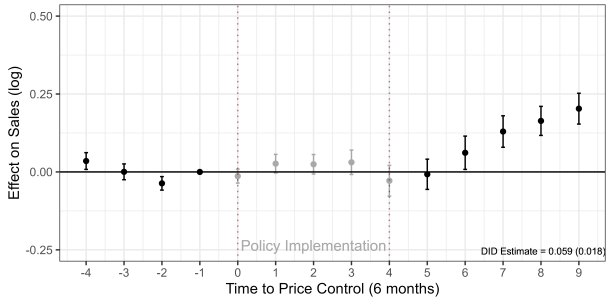
[20] See Supplementary Section A.2.2 for a complete description of the data.

[21] In Supplementary Figure B11, 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.

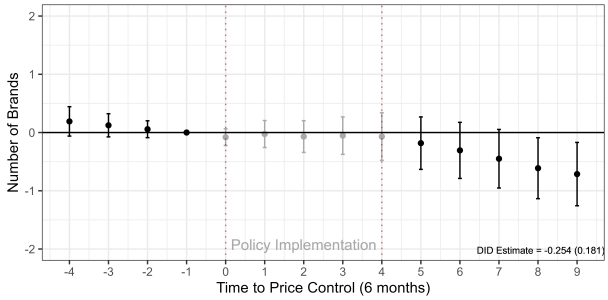
Figure 4: Effect of the Indian Policy on Sales, Product Availability, and Detailing



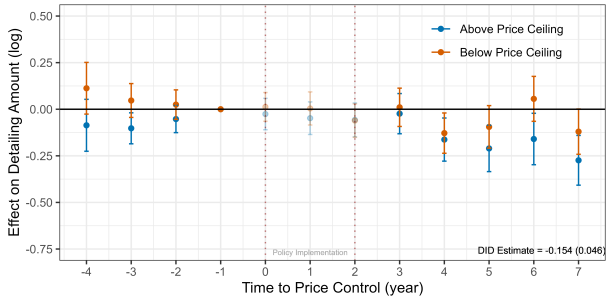
(a) Sales: Brand Level



(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 is the time from when the price control was implemented. 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 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 India 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.

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 (Supplementary Figure B21). However, this effect was short-lived and had completely dissipated by 2019. The 2019 amendment, which exempted patented drugs from price controls for five years, appears to have been effective in stemming this modest decline in drug diffusion. We further show that, beyond India, the policy did not

have an economically or statistically significant impact on the launch of new molecules or initiation of new clinical trials worldwide (Supplementary Figures B22 and B24). Similarly, the Indian policy had minimal impact on the stock prices or research and development expenditures for publicly listed pharmaceutical firms (Supplementary Figure B25).[22]

5 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.[23]

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.

[22] 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.

[23] 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 D.

We invited 69,702 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.[24]

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.[25]

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.

The third section assesses physician knowledge. We collect information on the ranking of their medical school, practice type, number of patients treated per week, hours worked per week, and answers to two clinical knowledge questions often asked in U.S. medical board examinations.[26] We also collect additional demographic information.[27]

5.2 Sample Characteristics

In Supplementary Table E1, 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).[28] 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%).

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

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

[26] We selected and validated these questions from materials used for US board examinations in consultation with physicians in both the U.S. and India.

[27] A copy of the survey instrument can be accessed at https://kellogg.qualtrics.com/jfe/form/SV_2mB7NknJD3YiH3g.

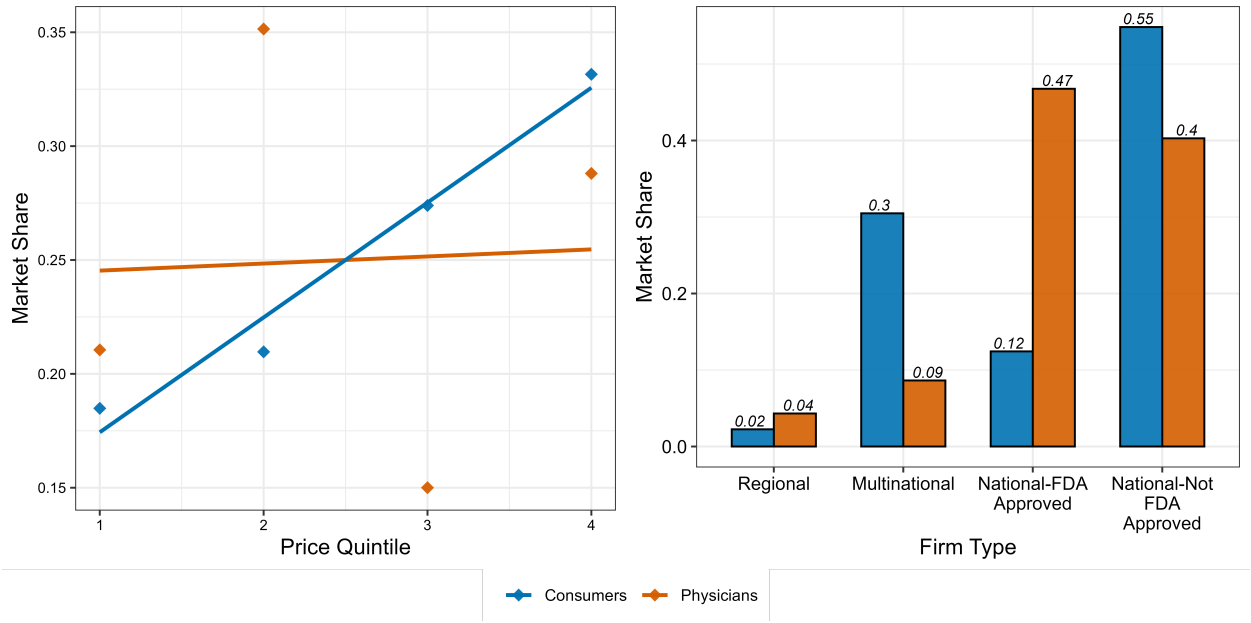
[28] We cannot directly evaluate the representativeness of our sample as there is no census of medical providers in India.

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

Figure 5: Descriptive Comparison of Physician and Consumer Choices



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

In the left panel of Figure 5, 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 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 prices or multinational status as proxies for quality.

Our qualitative questions provide additional insights into the factors underlying physicians' brand choices. The physicians report that they choose their preferred brand because it is easily available in their pharmacy (60%), has a good reputation (50%), and is of high quality (40%) (Supplementary Figure E1). 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 in our normative framework.

To further examine how choices vary with physician knowledge, we exploit multiple measures of expertise collected in our survey. In Supplementary Tables E2 and E3, 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 6.1.5, 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 many of the drugs regulated by the Indian policy. Supplementary Section F.1 details our selection criteria, discusses specific exclusions, and presents descriptive statistics for each market (Supplementary Table F1). We estimate the model separately for each therapeutic market. For clarity, we discuss the estimation procedure as if applied to a single market, and later present results by market.

6.1 Estimation

Our goal is to estimate the distribution of price sensitivity $H_s(\alpha_i)$, the perceived product utility δ, the nesting parameter ρ, marginal costs mc, and choice frictions δ^{fr}. The estimation proceeds in four steps. First, we specify a parametric form for the distribution of price sensitivity, $H_s(\alpha_i)$. Second, we estimate the demand parameters by matching observed sales changes associated with the 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 defined in Equation 3.4. Finally, we estimate choice frictions as the wedge between consumers' and physicians' perceived utility.

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.

6.1.1 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 C.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).[29]

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.

[29] We also estimated the model under alternative specifications and found that this formulation provided the best fit to the data.

6.1.2 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.[30] 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.[31] Supplementary Figure F1 presents empirical distribution of income by health status.

6.1.3 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 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.[32] 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

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

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

[32] 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.

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). 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.[33]

Supplementary Section F.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 rival' 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).[34] 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.

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 F2, 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 F5). Together, these findings support the assumption that changes in unobserved demand shocks are orthogonal to our instruments.

[33] 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.

[34] We test the relevance assumption in Supplementary Tables F2 and F3. We find that F-statistics of a regression of the instruments on price changes exceed 100 in all cases, alleviating concerns about weak 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: $\hat{\delta}_{js} = \frac{1}{T}\sum_{t=2011}^{2013} \delta_{js} + \xi_{jst}$.

6.1.4 Marginal Costs

We recover marginal costs, mc_{jst}, that rationalizes 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.

6.1.5 Choice Frictions

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

We maintain two key assumptions. First, we assume that

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

As discussed earlier, 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.

Differences in brand choices by consumers and physicians could reflect not only choice frictions but also other factors such as differences in income and price sensitivity. Therefore, we cannot directly infer choice frictions from observed market shares alone. To isolate choice frictions, we recover physicians' perceived utility δ^{phy} after adjusting for other determinants of demand.

We estimate the parameters for physician preferences $\{\alpha^{\text{phy}}, \rho^{\text{phy}}, \delta^{\text{phy}}\}$ by maximizing the likelihood of choices reported in our survey. Physicians reported their choices in three scenarios: their preferred product ("baseline choice"), the choice following a random price increase for the baseline product, and their choice when the baseline product is removed from the choice set ("second choices"). We specify physician preferences using the same utility function in Equation 3.1, which determines the model-implied choice probabilities as a function of $\{\alpha^{\text{phy}}, \rho^{\text{phy}}, \delta^{\text{phy}}\}$. Given the observed choices and model-implied conditional choice probabilities, we estimate the parameters via maximum likelihood. Supplementary Section F.4 provides further details on the likelihood construction and the estimation procedure.

With these estimates in hand, we recover choice frictions as the difference in perceived utility between patients and physicians: $\delta^{\text{fr}} = \delta - \delta^{\text{phy}}$. This measure relies on the following assumption:

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

Under this assumption, in the absence of frictions, consumers would make choices based on δ^{phy} instead of δ. The implied change in choice probabilities is: $\Delta\sigma_{ij|m} = \sigma_{ij|m}(p, \delta^{\text{phy}}|y_i, \alpha, \rho) - \sigma_{ij|m}(p, \delta|y_i, \alpha, \rho)$, which we refer to as the *choice wedge* going forward. While the consumer and physician choices may still differ because of differences in y_i, α, ρ, this assumption entails that any remaining difference in choices — holding these factors constant — reflects choice frictions.

This assumption may be violated if other welfare-relevant factors beyond income, α, and ρ influence brand choices and differ systematically between physicians and consumers. To assess this concern, we implemented an additional consumer survey targeting various consumer groups, including lawyers, government employees, and school teachers (Supplementary Section E.1.1). We find that brand choices do not vary systematically with sex, employment status, or industry, conditional on location and income (Supplementary Table E6). In contrast, more educated consumers and those who correctly define a generic drug are less likely to buy expensive brands. We also surveyed 60 pharmacists and found similar patterns: pharmacists, especially those with formal training and over one year of experience, are less likely to buy expensive brands (Supplementary Table E7). These findings further suggest that observed differences in brand choices are partly driven by choice frictions, while unmodeled preference heterogeneity plays a limited role.

6.2 Results

Consumer and Physician Preferences 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($\rho \geq 0.50$).

In most cases, physicians are less price sensitive than consumers and less willing to substitute across molecules. This low price sensitivity suggests that the physicians' choices for their own treatment are primarily driven by their beliefs about product quality, δ^{phy}. This finding is consistent with the qualitative evidence described earlier: only a small fraction of physicians cite low prices as an important factor in their choices (Supplementary Figure E1).

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.[35] Markups are the highest in the diabetes and CCB

[35]See Supplementary Figure F3 for the full distribution of marginal costs in each market.

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.

Table 1: Estimated Parameters and Summary Statistics of Model Primitives

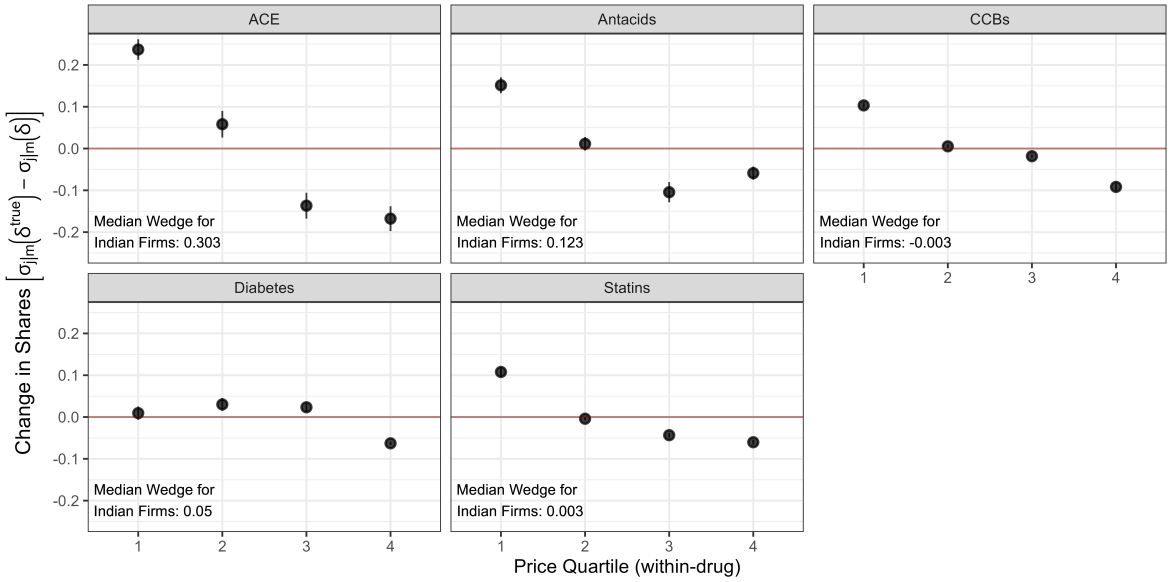
	ACE	Antacids	CCBs	Diabetes	Statins
Consumer Preference Params.					
α_g	34	80.03	20.06	23.38	20.88
	(0.014)	(0.001)	(0.004)	(0.002)	(0.001)
α_p	13.74	20.01	60.08	23.31	19.95
	(0.042)	(0.001)	(0.003)	(0.001)	(0.001)
ρ	0.57	0.53	0.5	0.28	0.19
	(0.026)	(0.001)	(0.002)	(0.001)	(0.001)
Physician Preference 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 6 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.[36] These patterns have important welfare implications, as the Indian policy generated the largest price reductions for these expensive brands (Supplementary Figure F7).

[36]See Supplementary Figure F4 and Supplementary Table F4 for the companies with the most and least bias.

Figure 6: Price Differences and Choice Wedges



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

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). We also find that the variation *perceived* utility exceeds that in *true* utility in most therapeutic markets, suggesting that choice frictions may have generated spurious product differentiation and exacerbated market power.

Correlation Between Costs and True Quality We find a positive correlation between marginal costs and true product quality across all five therapeutic markets, suggesting that stringent price controls may lead to the exit of high-quality products and generate negative welfare consequences.

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 F5, the model correctly predicts 87% – 96% of observed exits across therapeutic markets. For products with a pre-policy market

shares 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 B20).

In Supplementary Table F6, 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.

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.[37] 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 7 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.

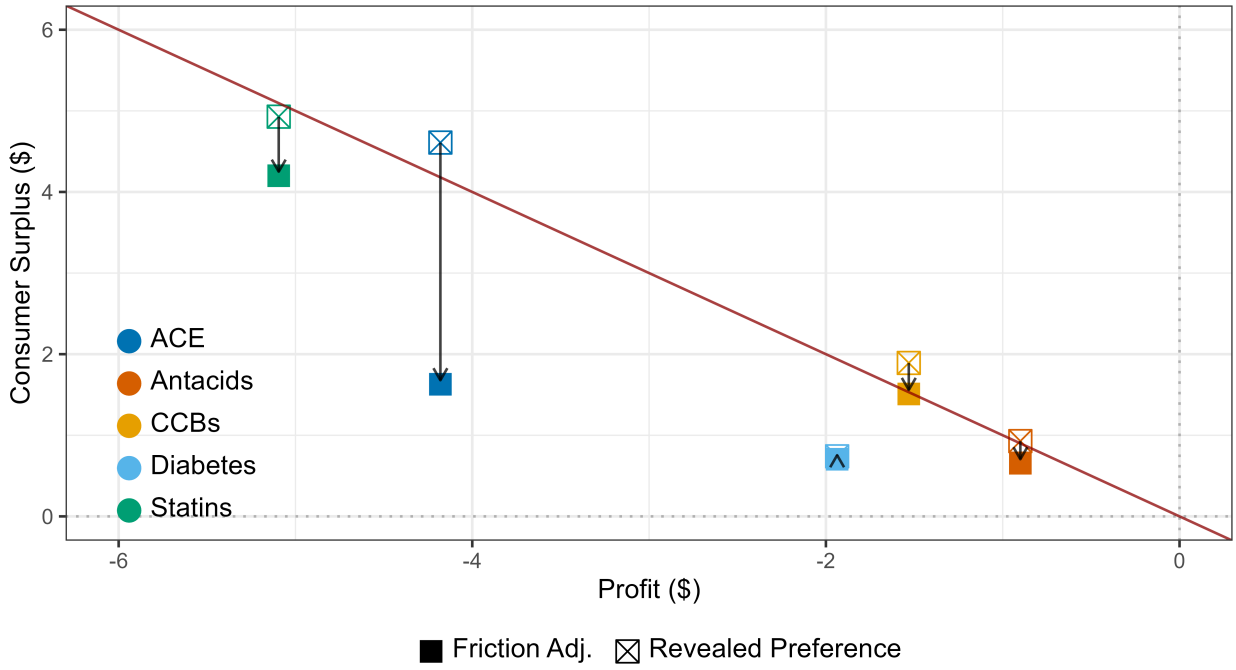
The price ceilings increased drug consumption without triggering many product exits. The increase in consumption is particularly pronounced in the ACE inhibitor and statins markets, where price reductions were larger and consumers more price sensitive. Notably, the policy increased the total consumption of regulated, essential drugs by between 3% and 10%. Overall, the Indian policy accomplished its central objective of improving access to essential medicines.[38] 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

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

[38] 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 7: 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

expensive brands now pay less because of lower prices. In our model, these consumers tend to be sicker and wealthier (Supplementary Figure F6). 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 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.

The Indian policy exhibited two key shortcomings. First, it was poorly targeted: it generated the largest price reductions for products that consumers tend to overvalue. Second, the policy lacked flexibility, imposing a uniform price ceiling across all brands of a given drug. While exit was limited in this case, further tightening of the uniform price ceiling risks triggering exits of high-quality products, which typically have higher marginal costs.

7.2 Choosing Price Ceilings

Price control is not a binary policy: importantly, regulators must choose the level of 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 8.

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 prepolicy markups. In the CCB market, where markups are high, ceilings set at as low as the 20^{th} percentile of the prepolicy 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.

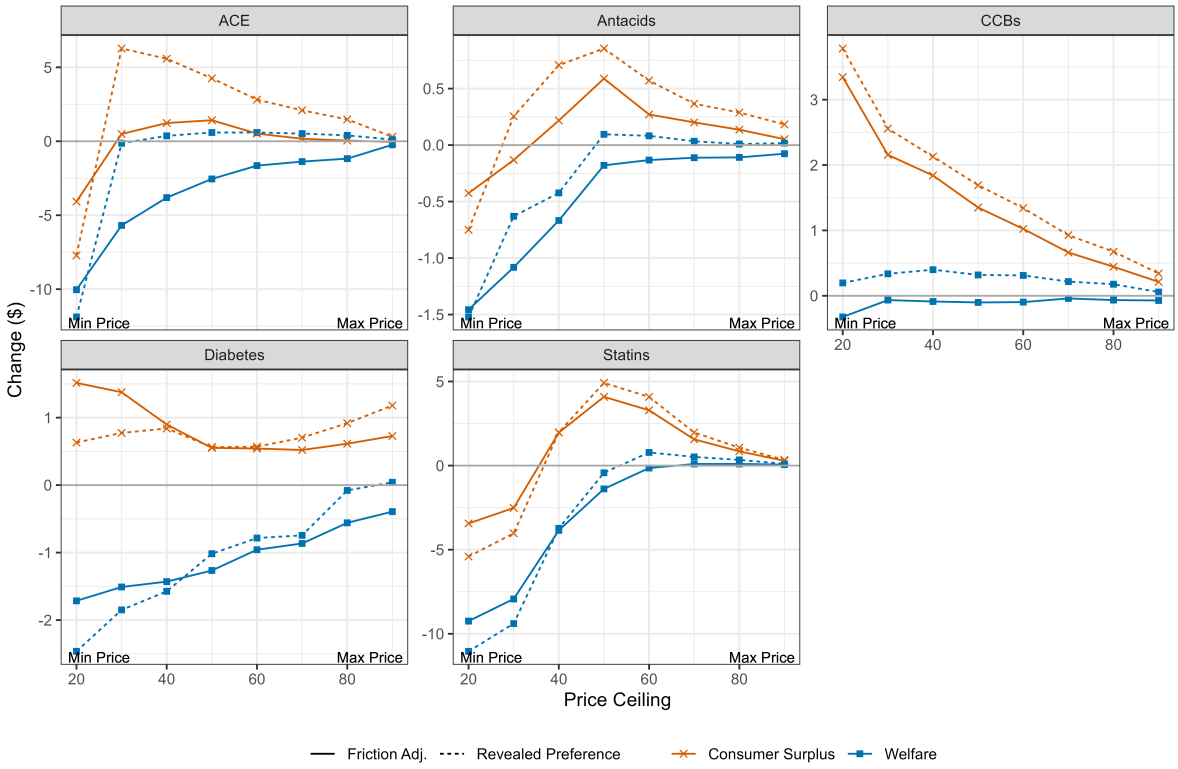
As with the Indian policy, we find that the consumer surplus gains from drug-level price ceilings are typically smaller than those implied by revealed preference, and that true social welfare generally declines. By design, *any* drug-level price ceiling imposes larger price cuts on higher-priced products—precisely 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.[39] 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 F.8) and empirically (Supplementary Table F10).[40] An alternative or complementary approach is to reduce choice frictions, which we discuss next.

[39] 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.

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

Figure 8: 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.

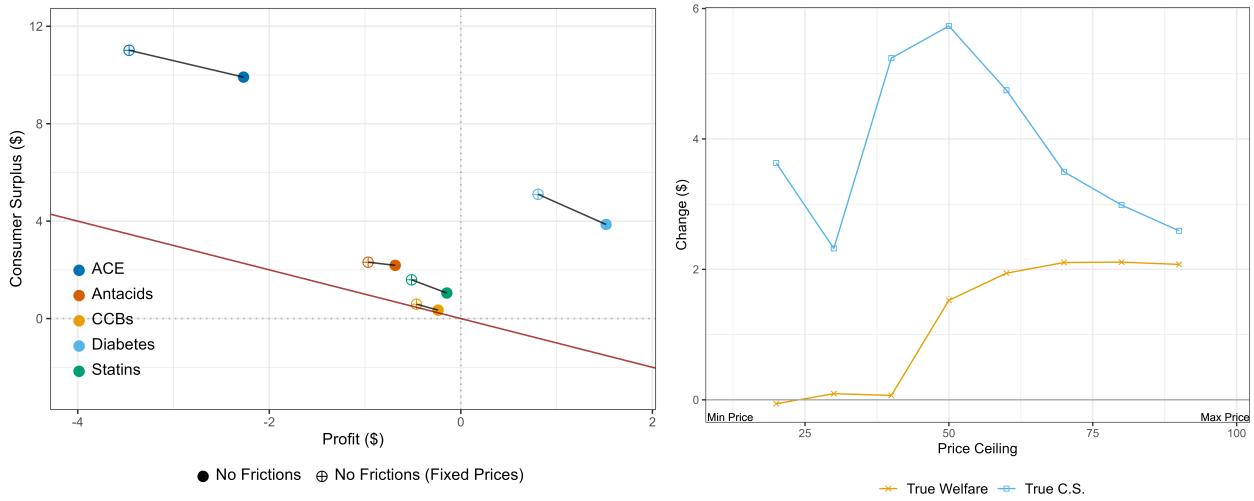
7.3 Reducing Choice Frictions

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 9.[41]

Figure 9: Impacts of Eliminating Choice Frictions

(a) Without Price Ceilings

(b) With Price Ceilings



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

In our first counterfactual, consumers 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 F7). 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

[41] 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 E3 and E4). 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.

some consumer surplus (Supplementary Figure F8). The impact on total social welfare remains similar to the case where prices remain unchanged (Supplementary Table F8).

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 importance 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 F9).[42] 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 9b 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 F10. 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.

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 F.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.

[42] Supplementary Table F9 reports the share of first-best surplus gains achieved under all policy scenarios.

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 F.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 F.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 externality 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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Online Supplementary Materials for
Price Controls with Imperfect Competition and Choice Frictions:
Evidence from Indian Pharmaceuticals

September 16, 2025

Contents

A Data Appendix

A.1 AIOCD Data

Sample Construction We apply several steps to process the raw data for our analysis. In the raw data, the unit of observation is a Stock Keeping Unit (SKU). A SKU is a combination of company, molecule(s), dosage, administrative route, and package size. We restricted the sample to include only single-molecule products sold in the form of a tablet or capsule. We exclude topical, injectable, or liquid products because they are a tiny share of the market. We exclude fixed-dose combinations as they were not regulated by the Indian Policy. We aggregated to the company-molecule-dosage level, abstracting away from package size and administrative route.

Observed Prices In these data, we observe the prices and sales of transactions that occur between manufacturers and retail pharmacists through stockists. In theory, the retail prices that consumers are charged could exceed the prices we observe, and given the lack of comprehensive data on consumer-level transactions, we cannot directly examine the role of retail margins. This measurement issue may introduce noise in our estimate, but that variation in retail margins is likely limited for two reasons. First, retail prices are bounded above by "maximum retail prices", which are set by the manufacturers. In addition, retail margins were capped at 16% for drugs under price control. Thus, the scope of retailers to capture the surplus from the reduction in prices from the the Indian Policy is capped. More broadly, as we discussed above, retailers are small operations with limited market power, likely limiting their ability to influence prices. For antiobiotics in Bengaluru, Bennett and Yin (2019) estimate retail margins ranging from 5% to 15%.

A.2 Supplementary Data Sets

A.2.1 Citeline Pharmaprojects

We collect data on drug development and launches using Pharmaprojects. Pharmaprojects is a commercial dataset developed by Citeline, a market intelligence company. Citeline employees collect drug information from company websites, reports, and press releases. Each company covered in the database verifies information related to drugs in the development pipeline.

Pharmaprojects provides information for each molecule that a company is attempting to develop. We observe molecule characteristics such as therapeutic class, targeted disease, generic name, proprietary name, and the firm that is trying to develop the molecule.

Pharmaprojects tracks the development activities of each molecule over time. We observe clinical trials, licensing agreements, and most importantly, for our purposes, whether a molecule was approved and launched in any given country.

Our dataset covers drug development from January 1, 2024, to December 31, 2020.

A.2.2 IQVIA ChannelDynamics

The IQVIA ChannelDynamics is a proprietary dataset developed by IQVIA, a leading pharmaceutical market intelligence company. The dataset measures pharmaceutical promotion activities ("detailing") based on a panel of 467 physicians in India (as well as other countries).

IQVIA records the promotional activities performed by a firm (e.g., Pfizers) for its different products. They record the amount of money spent on different types of promotional activities, such as face-to-face meetings, details, free samples, etc., per year in India. We observe these variables at monthly frequency between January 1, 2012, and December 31, 2019.

A.2.3 Longitudinal Ageing Survey of India

The Longitudinal Ageing Survey of India (LASI) is a comprehensive survey of the economic, social and health of Indians 45 years of age or older. LASI is India's first and largest longitudinal ageing survey in the world, and is comparable to the Health and Retirement Study (HRS) in the United States. LASI is a collobaration between several academic and governmental institutions, including the Ministry of Health and Family Welfare, the United Nations Population Fund, International Institute for Population Sciences, and Harvard T. H. Chan School of Public Health, and University of Southern California.

We access the first wave of LASI, which was conducted between April 2017 and December 2018. LASI Wave 1 is a nationally representative survey of 73,396 adults aged 45 and older in all states and union territories of India. The first wave collected detailed questions about demographics, financial assets and debts, health insurance, healthcare utilization, and community information. Critically for our purposes, the survey included information on whether individuals suffered from a rich set of diseases, their health status on a discrete five-point scale, their income, and health as well as non-health expenditures.

The health status is recorded on a five-point scale based on the question "overall, how is your health in general? Would you say it is very good, good, fair, poor, or very poor". Self-reported health (SRH) is widely used as an epidemiological instrument for measuring public health, especially when measures of physical illness and other objective health measures are lacking (Lorem et al., 2020). We transform this five-point scale to a binary scale.

LASI is publicly and freely available to researchers, upon approval from the IIPS. We accessed the data using the following website: LASI Data.

A.2.4 National Social Survey: Health 71st Round

The National Social Survey: Health (NSS) is a comprehensive and nationally representative survey conducted by the Indian Government. The 71st Round of this survey was conducted between January 2014 and June 2014.

This health survey aims to collect quantitative data on the health sector, focusing on the prevalence of diseases among different age and sex groups in various regions. The survey examines the types of ailments treated, the extent of government hospital usage, and the costs incurred for treatment in both public and private sectors, including a detailed breakdown of these expenses.

We access the data directly from the National Data Archive developed by the Indian Ministry of Statistics and Programme Implementation.

A.2.5 Regulation Status and Price Ceilings

The set of price controls were obtained from public announcements by National Pharmaceutical Pricing Authority of India on June 15th, 2022 (Link). The data from these announcements were then manually coded.

B Descriptive Evidence

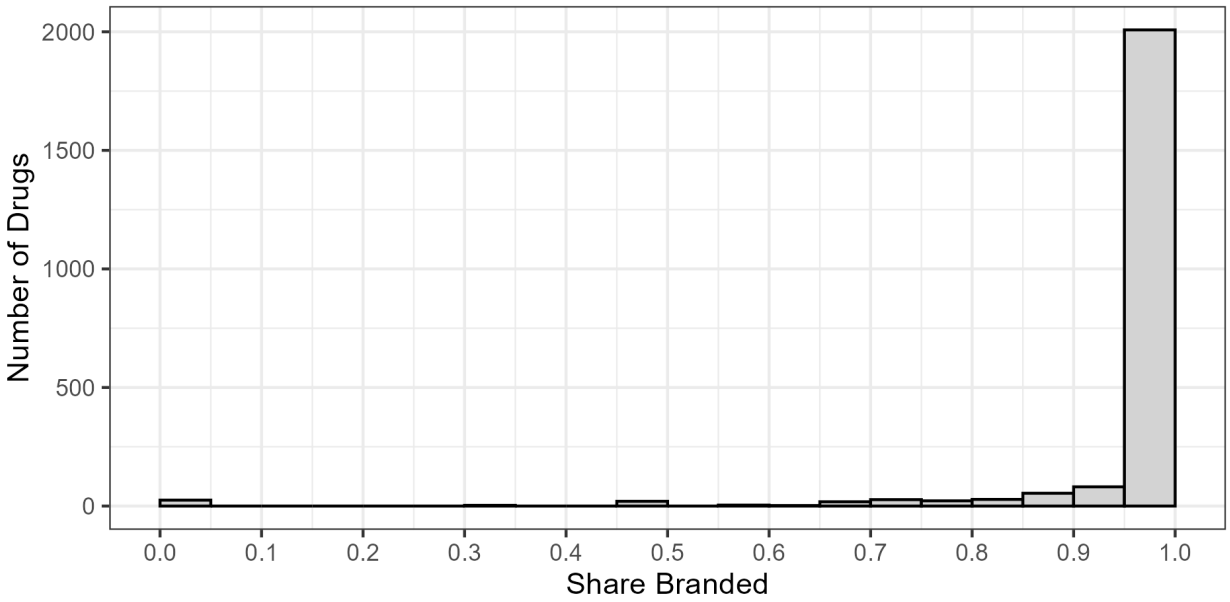
B.1 Indian Pharmaceutical Market

Table B1: Characteristics of Firms

	Multinational	**National**	**Regional**
N	9	74	691
Num. Mols.			
Median (IQR)	34 (20 - 68)	56 (42 - 93)	6 (3 - 12)
Num. States			
Median (IQR)	29 (29 - 29)	29 (29 - 29)	5 (2 - 12)
Annual Revenue (Rs. Millions)			
Mean (SD)	2,578 (2,974)	2,141 (3,201)	22 (116)
Median (IQR)	1,011 (494 - 3,406)	492 (168 - 2,926)	0 (0 - 4)
Sell Any Mol. in US	0.89	0.34	0.02
Mols Sold in US (median)	5	8	2

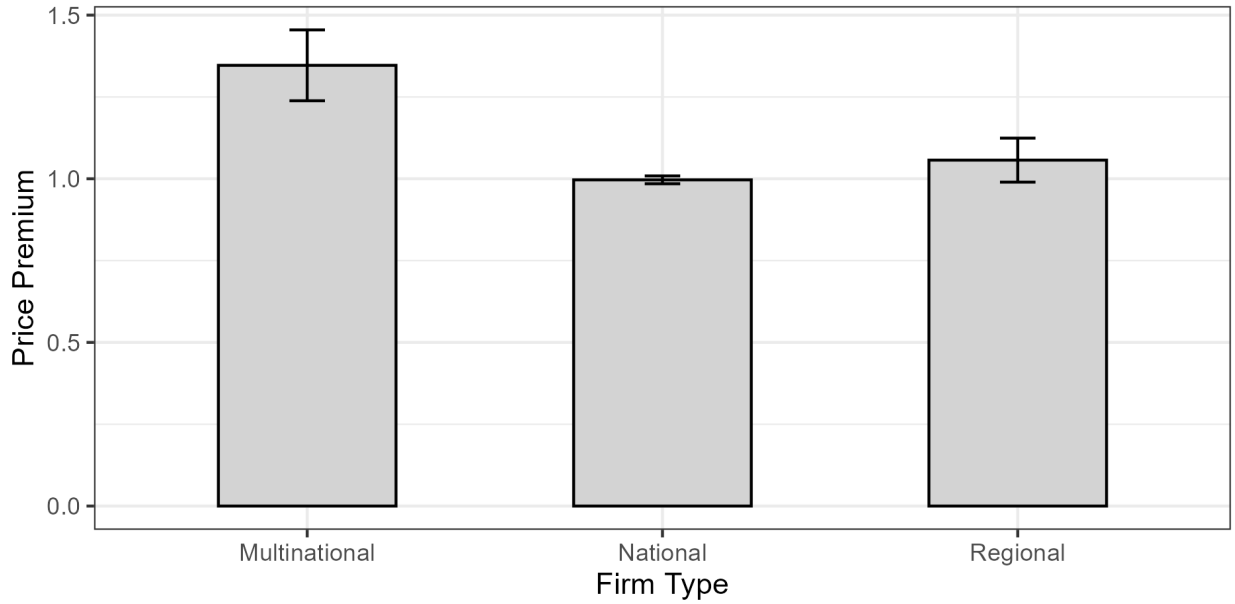
Notes: The table present descriptive statistics of the firms in the AIOCD data in 2011, by a classification of firms into multinational, national, and regional. Each observation is a firm that manufactures "Num. Mols" distinct molecules and supplies it in "Num. States" out 29 states in India. A firm may also "Sell Any Mol. in US". If a firm sells at least one molecule in the US, then " Mols Sold in US" measures the number of molecules they sell.

Figure B1: Share of Manufacturers with a Brand Name Across Drugs



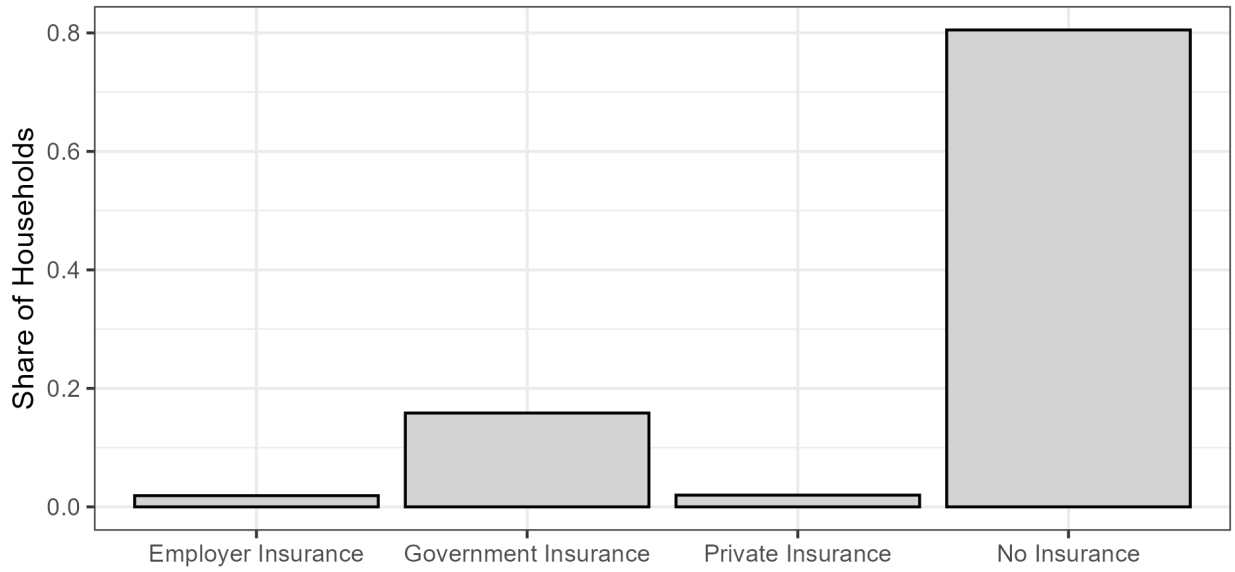
Notes: The figure presents distribution of the share of manufacturers that sell under a brand name across drugs.

Figure B2: Price Premium by Firm Type



Notes: The figure presents mean price premium for different firm types based on data in 2012. Firms are classified into into multinational, national, and regional. Price premium is a firm's price for a drug divided by the mean price of all other firms selling the same drug.The bars denote 95% confidence intervals.

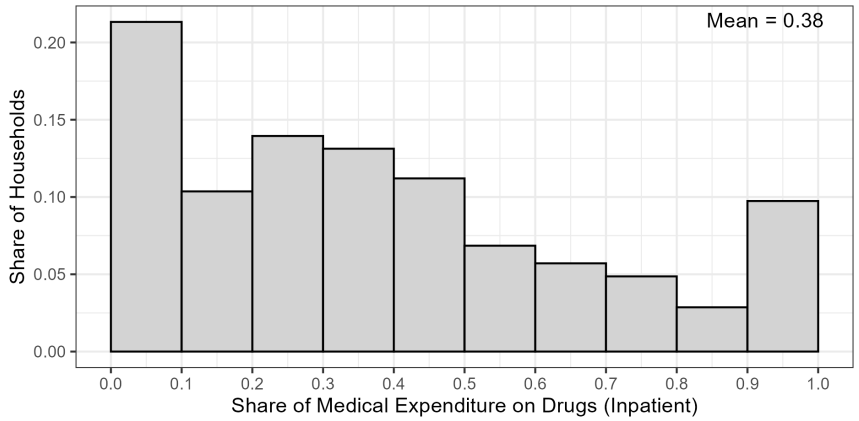
Figure B3: Prevalence of insurance coverage in India



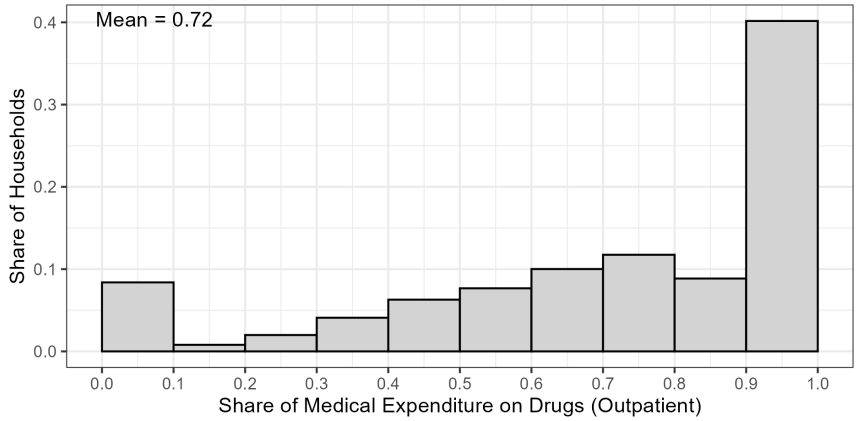
Notes: The figures present the share of households that reported receiving health insurance from their employer ("Employer Insurance"), from the Indian government ("Government Insurance"), from private insurance companies ("Private Insurance"), and that reported received no insurance coverage ("No Insurance"). Data source: NSS Health 2014-2015 (Government of India, 2015)

Figure B4: Drug expenditure as a share of total health expenditure

(a) Inpatient

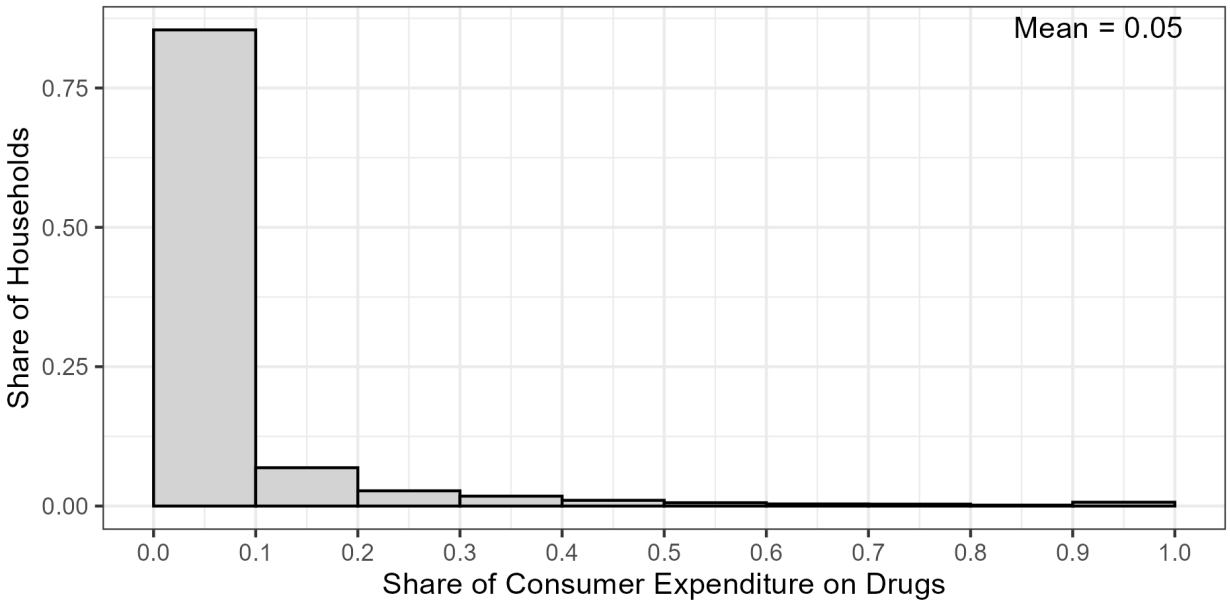


(b) Outpatient



Notes: The figures present the histogram of the share of overall health expenditure on drug expenditure, for inpatient (top panel) and outpatient (bottom panel) care. Data source: NSS Health 2014-2015 (Government of India, 2015).

Figure B5: The share of total consumer expenditure attributed to drug expenditures



Notes: The figures present the histogram of the share of drug expenditure of total consumer expenditure. The mean for the sample is annotated in the figures. Data source: NSS Health 2014-2015 (Government of India, 2015)

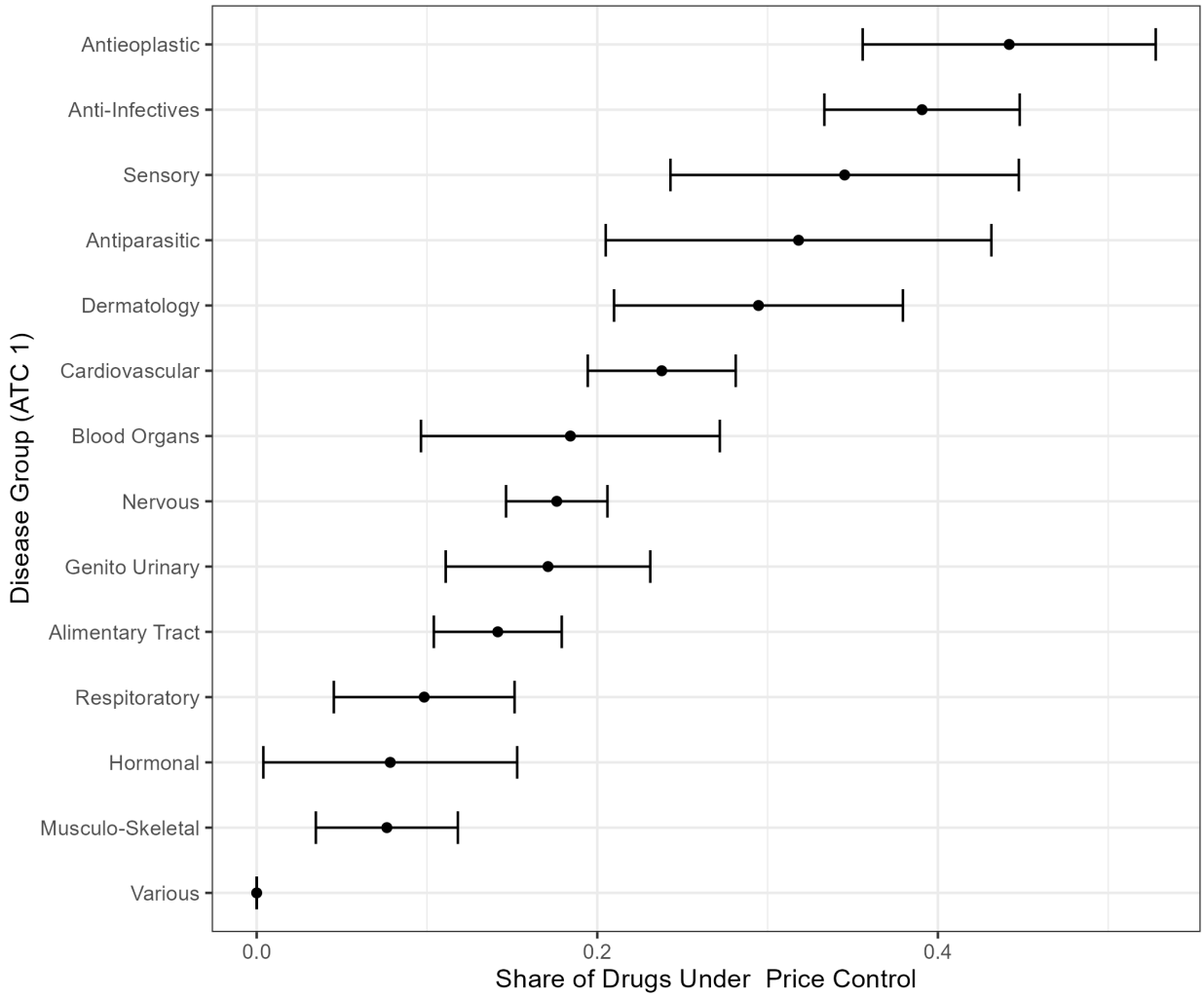
B.2 Indian Price Control Policy

Table B2: Descriptive Statistics of Drugs by Regulation Status

	Regulated	Competitors Regulated	Not Regulated
N	339	1,014	308
Price per pill	27.56 (188.73)	30.08 (278.72)	17.22 (54.23)
Sales (log)	15.57 (2.87)	13.26 (3.18)	13.40 (2.88)
Years Since Launch	20.41 (10.20)	15.80 (10.17)	13.28 (9.33)
Num. Brands	11.56 (12.03)	5.96 (7.76)	4.79 (6.46)
Only 1 Brand	0.11	0.31	0.34

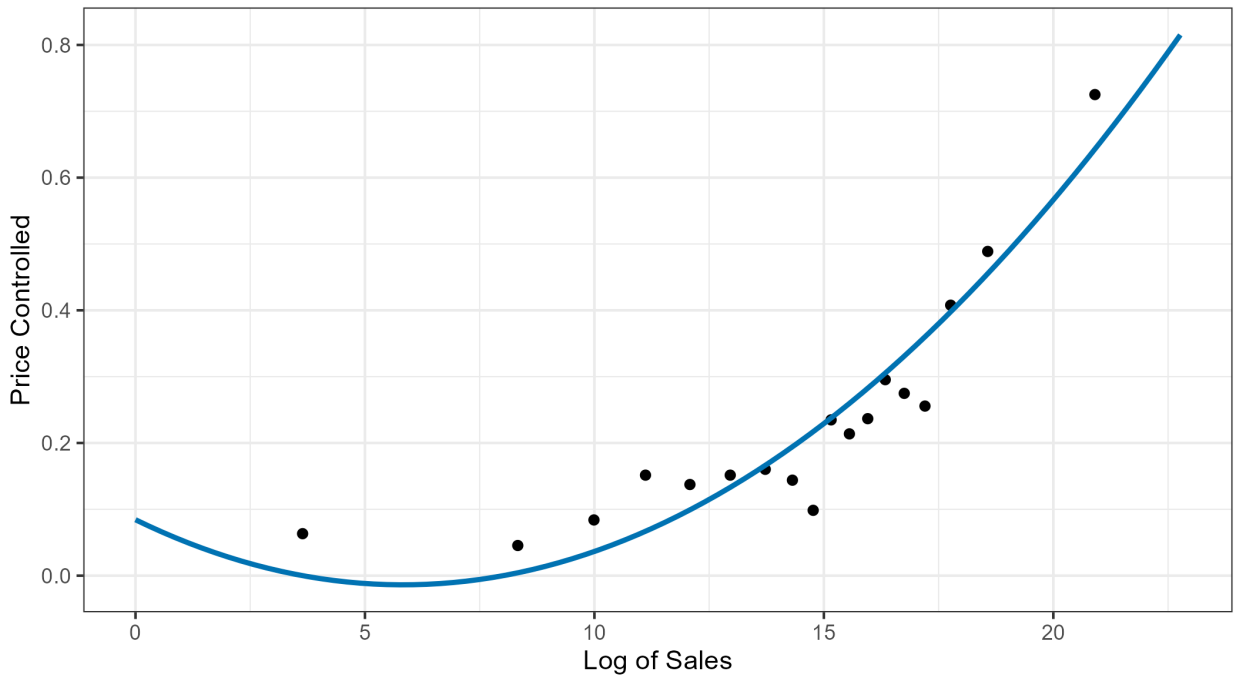
Notes: The table presents descriptive statistics for drugs that were regulated by the the Indian Policy ("Regulated), were unregulated but in the same disease as at least one regulated drug ("Competitors Regulated"), and were in a disease where no drugs was regulated ("Note Regulated"). An observation is a drug. The table presents the mean and standard deviations, with the exception of the row "Only 1 Brand", which presents the share of drugs where there was only 1 brand.

Figure B6: The share of drugs that are price controlled for different diseases



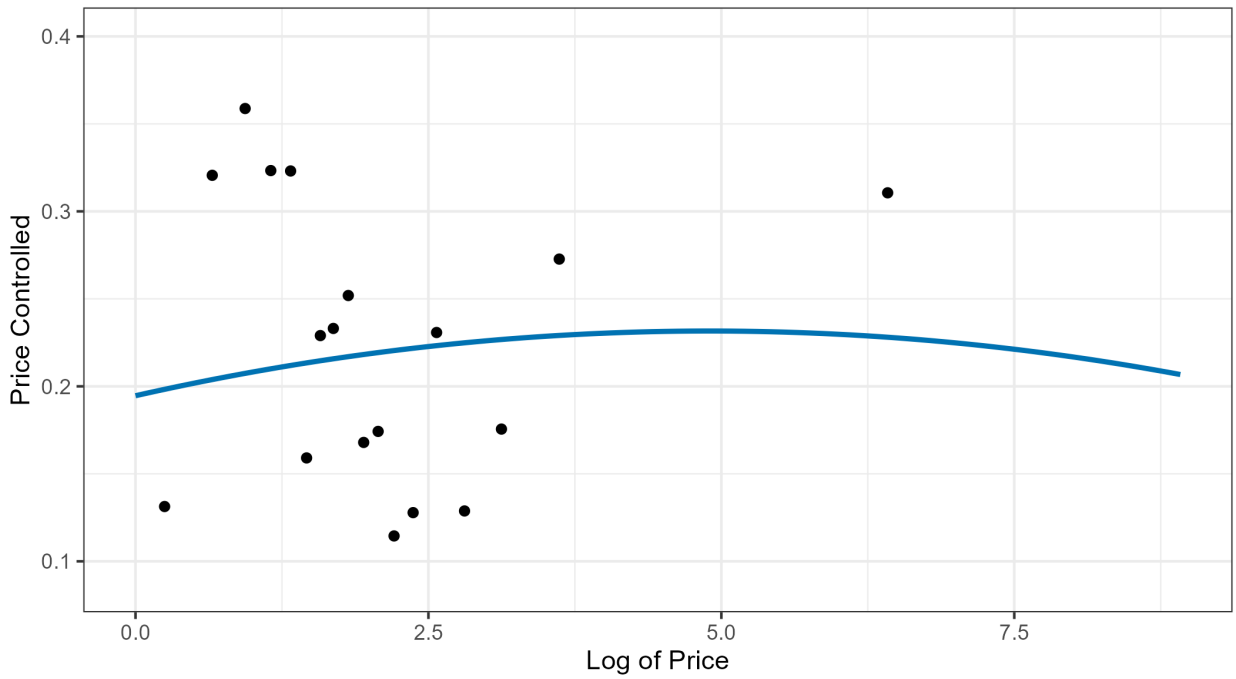
Notes: The figure presents the share of drugs put under price control on the $x-$axis for different disease groups, as denoted on the $y-$axis. A disease is defined as a unique ATC-1 code. The error bars denote 95% confidence intervals.

Figure B7: Relationship between sales and price controls



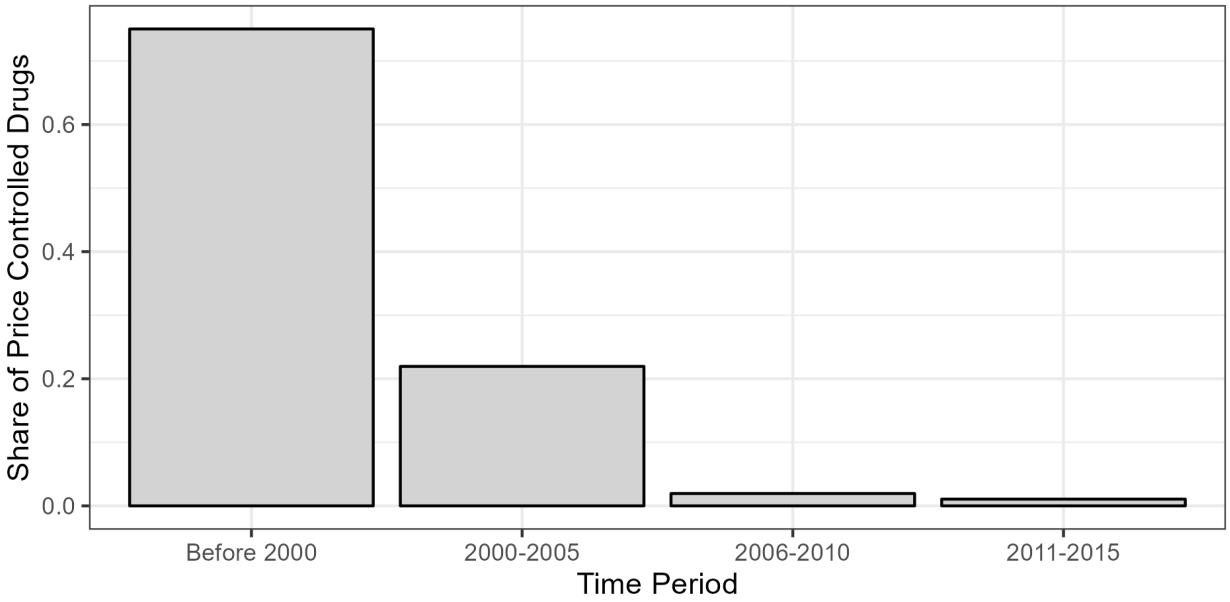
Notes: The figure presents a bin-scatter of the sales of a drug on the $x-$axis and whether the drug was put under price control on the $y-$axis. Each observation is a drug. The sales are computed as annual sales in 2012 on a log scale. The bins are chosen such that each bin has the same number of observations. A fitted second-degree polynomial is shown in blue.

Figure B8: Relationship between prices and price controls



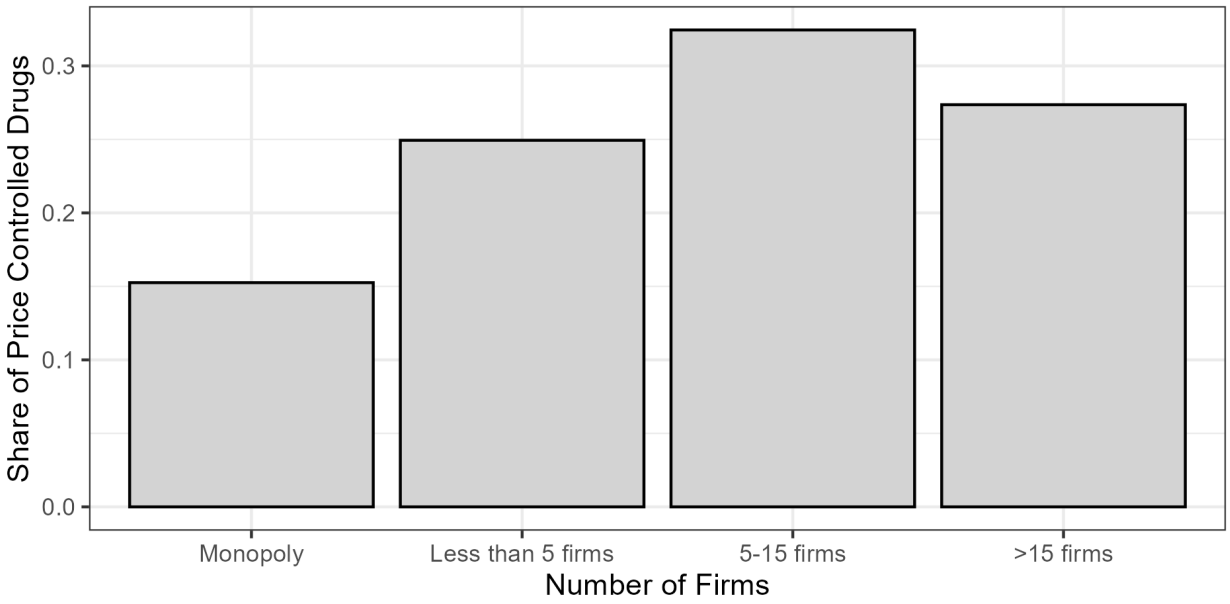
Notes: The figure presents a bin-scatter of the prices of a drug on the $x-$axis and whether the drug was put under price control on the $y-$axis. Each observation is a drug. The prices are computed as mean sales-weighted prices in 2012 on a log scale. The bins are chosen such that each bin has the same number of observations. A fitted second-degree polynomial is shown in blue.

Figure B9: The launch period for price-controlled drugs



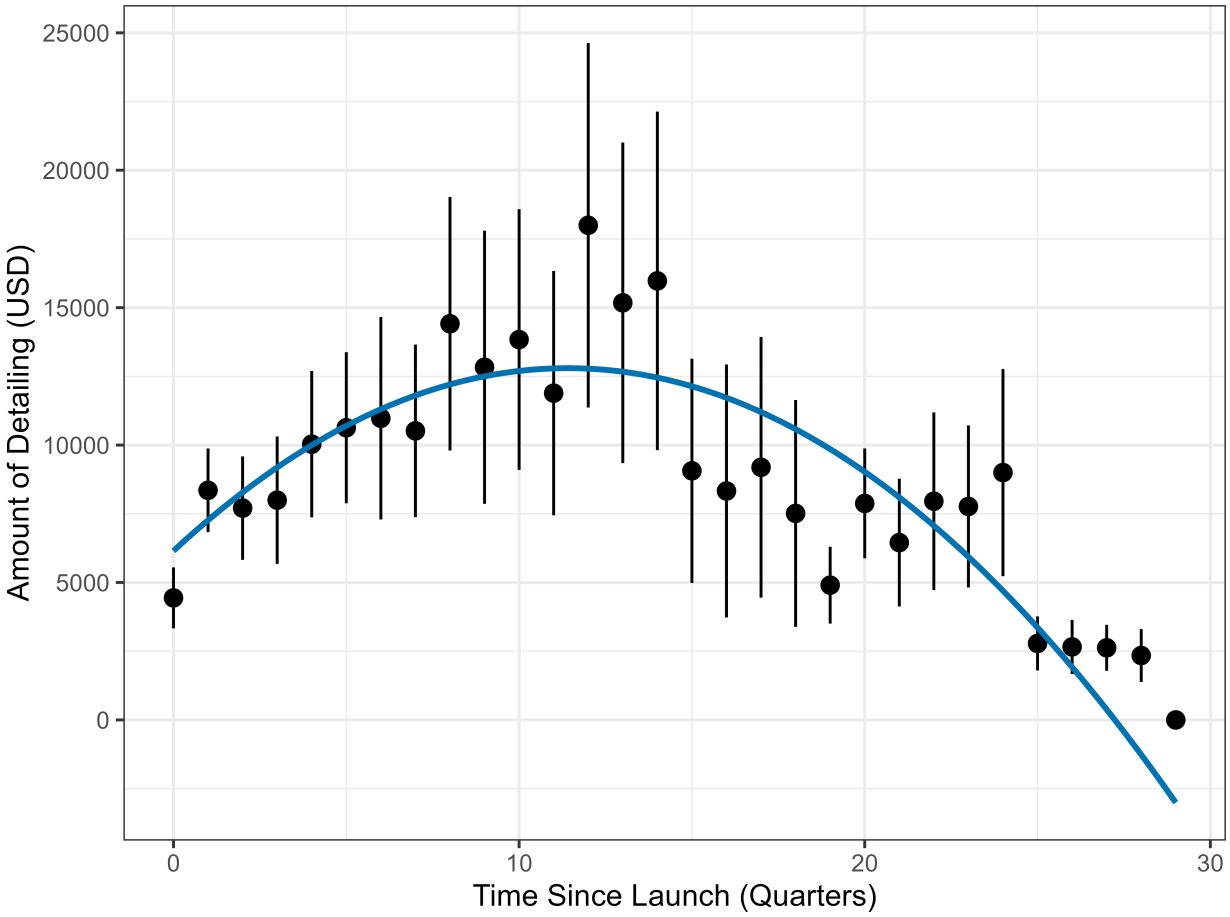
Notes: The figure presents the share of price-controlled drugs launched in different time periods.

Figure B10: The number of manufacturers for price-controlled drugs



Notes: The figure presents the share of price-controlled drugs for a different number of manufacturers in 2012.

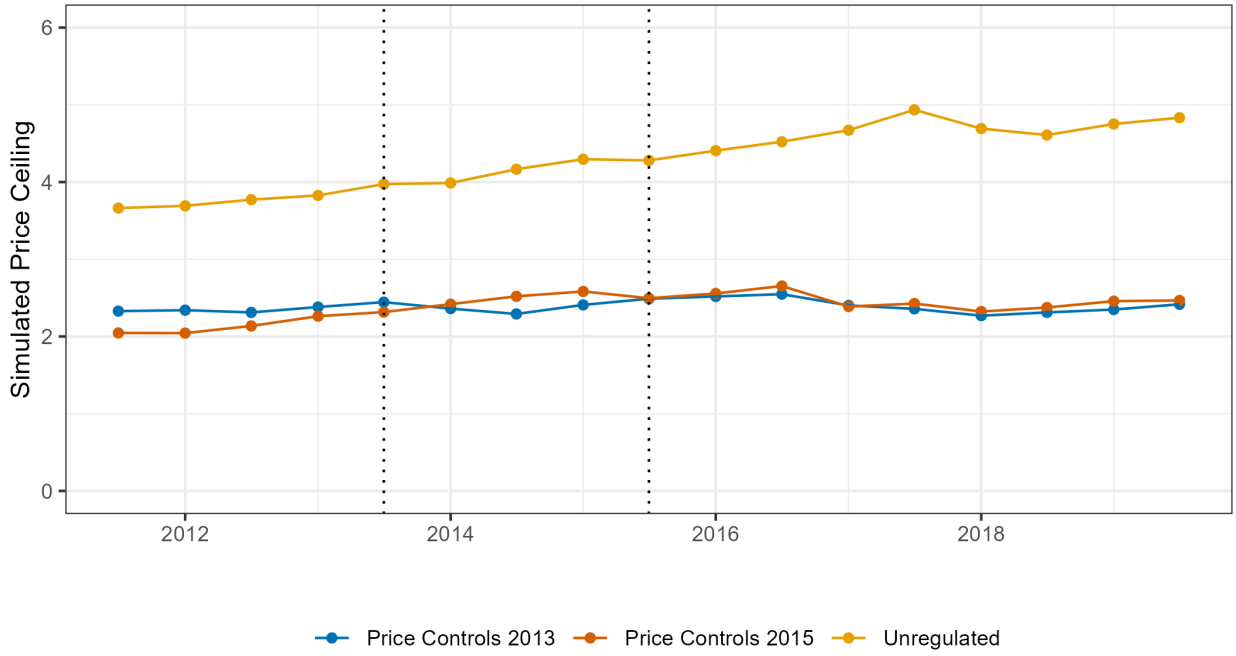
Figure B11: Trends in detailing over time



Notes: The figure presents the mean amount of detailing ($) for a given molecule on the $x-$axis for a specified time period after its launch in India on the $y-$axis. The unit of analysis is a molecule. "Time Since Launch" is calendar time relative to the time since a molecule was launched in quarters (3 months). The bars denote 95% confidence intervals

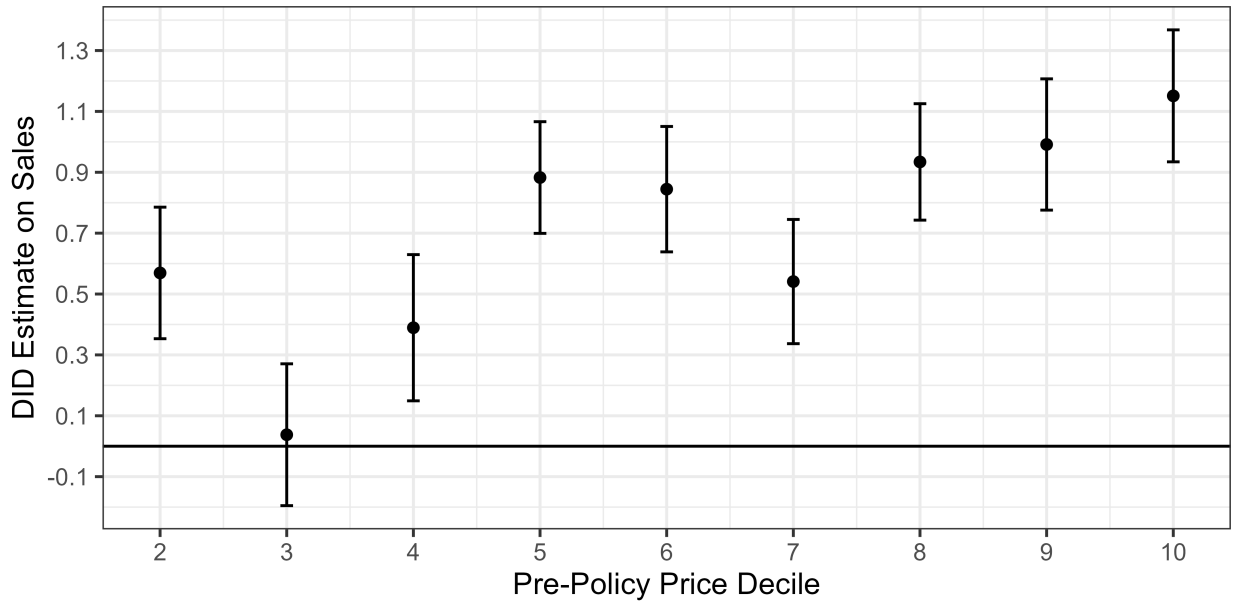
B.3 Additional Results and Robustness Checks

Figure B12: Trends in simulated price ceilings



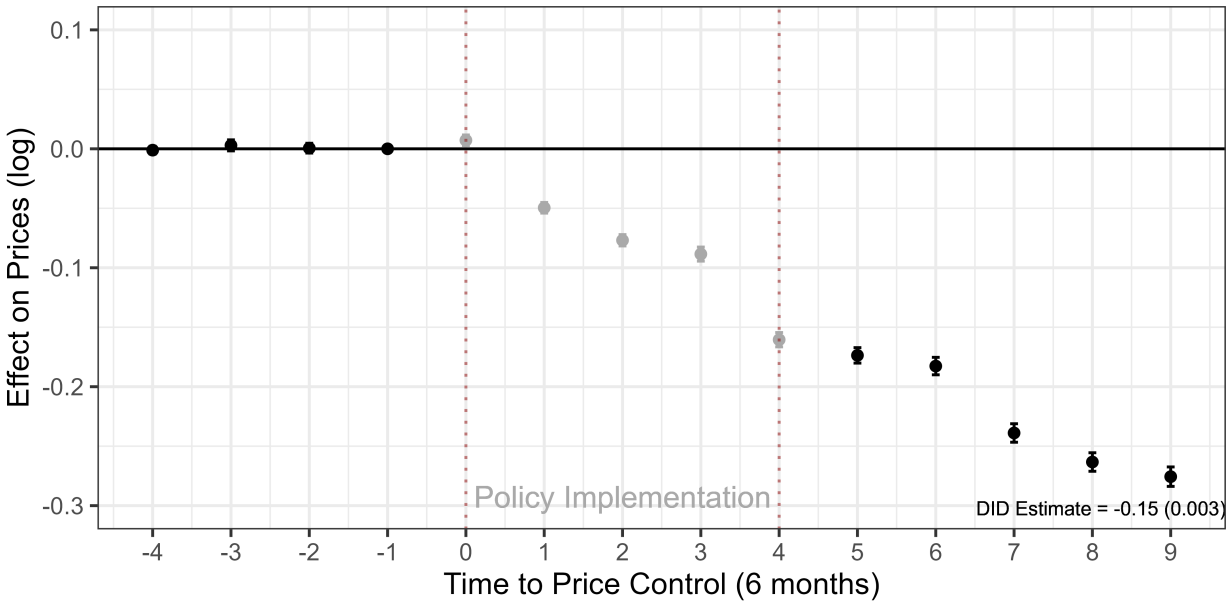
Notes: The figure presents the mean simulated price ceilings for different time periods. The $x-$axis represents a 6-month time period and the $y-$ axis represents the mean simulated price ceiling across drugs, where the simulated price ceiling for a drug in the mean price of all the brands of the drug in the corresponding period. Different colors denote different regulation status. The vertical lines denote the two waves of price controls in 2013 and 2015.

Figure B13: Heterogeneity in sales effects of the Indian Policy by pre-policy price deciles



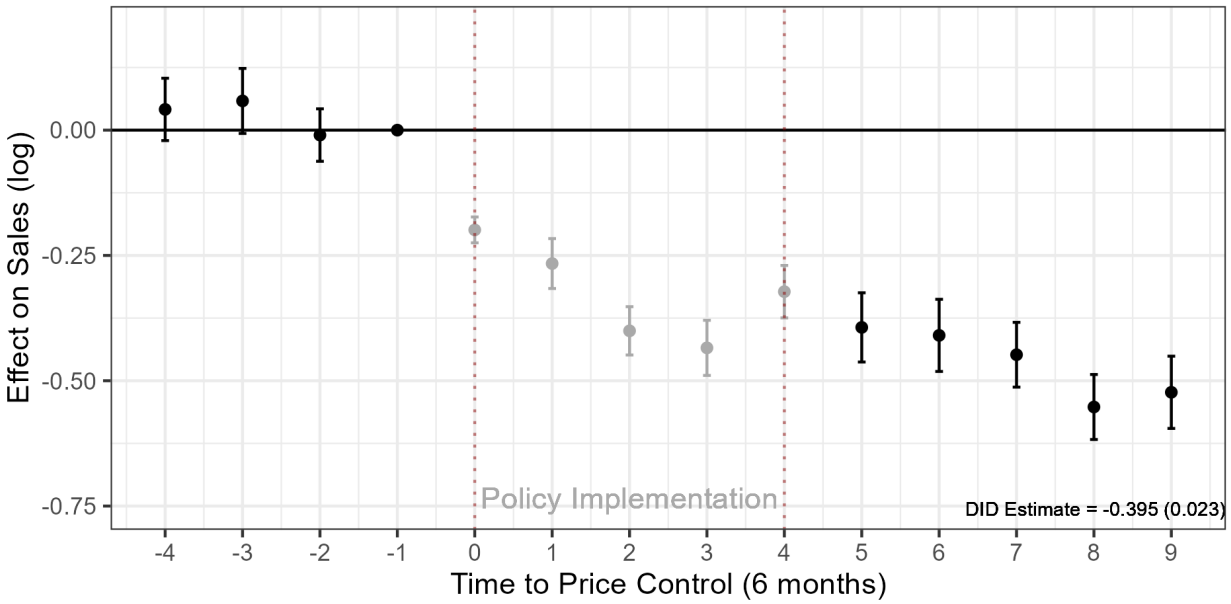
Notes: The figure presents the Difference-In-Differences estimate of the effect of the Indian Policy on sales (log) for different pre-policy price deciles 2012. The $x-$axis denotes the decile of price premia in 2012 and The $y-$axis denotes the DID point estimate and 95% confidence intervals.

Figure B14: The effect of the Indian Policy on prices at the drug level



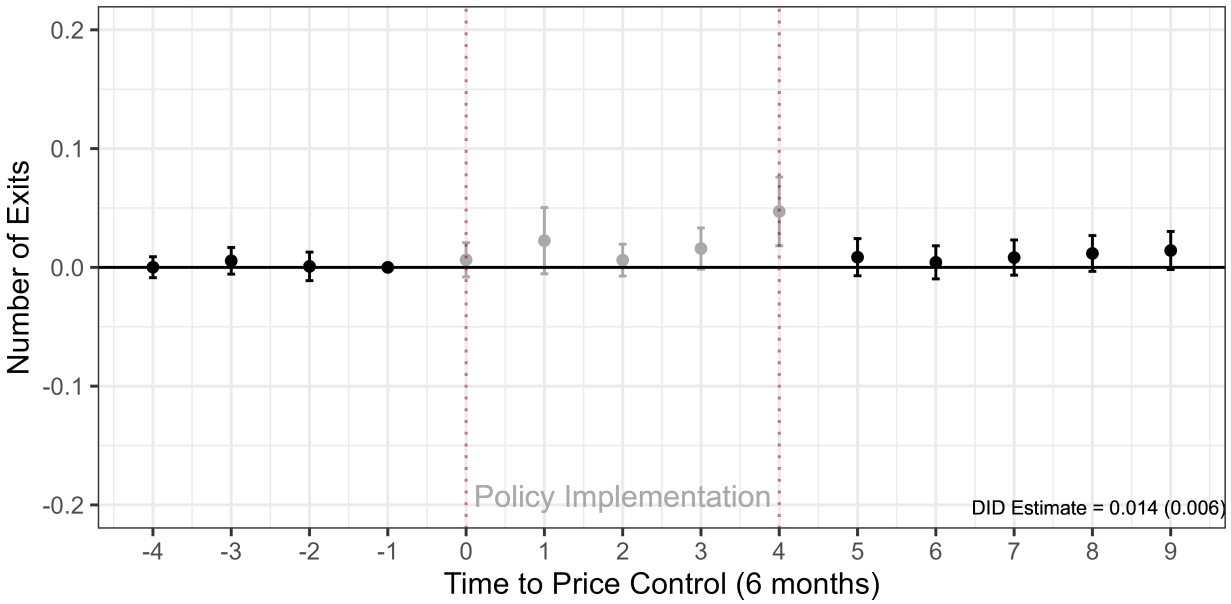
Notes: The figure presents the dynamic effects of the price control policy on prices. The $x-$axis is the time from when the price control was implemented (in years). The $y-$axis shows the ATT estimates with 95% confidence intervals. Each observation is a drug-state-year. The standard errors are clustered at the drug level.

Figure B15: Effect of the Indian Policy on drug-level consumption of competitors



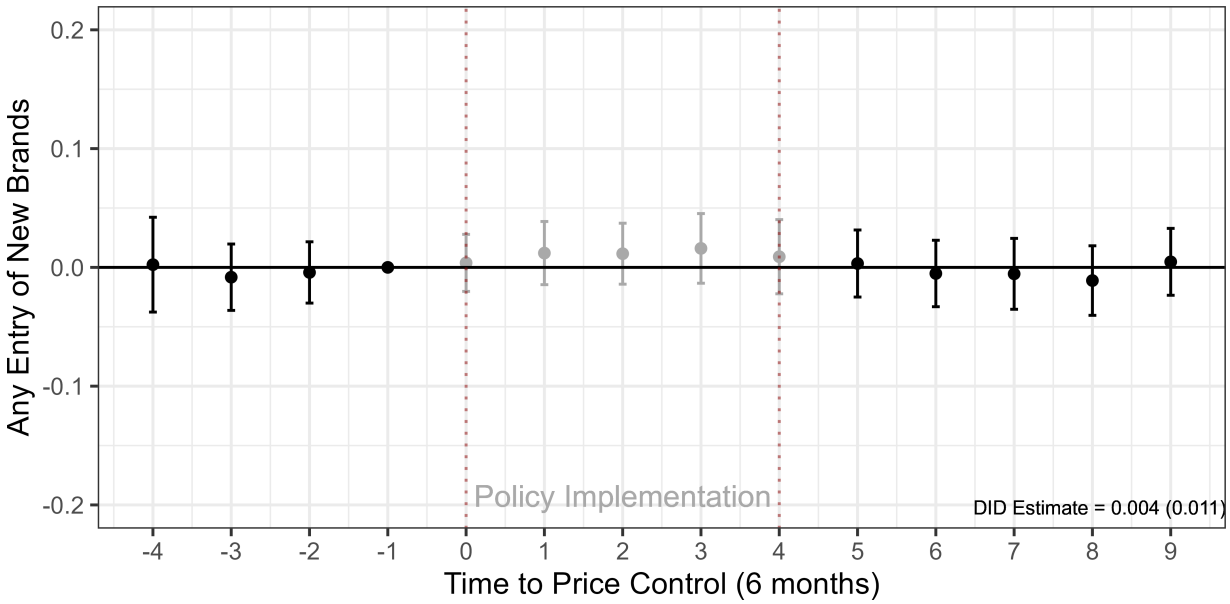
Notes: The figure presents the dynamic effects of the price control policy on sales for competitors of the treated drug. The $x-$axis is the time from when the price control was implemented (in 6 months). The $y-$axis shows the ATT estimates with 95% confidence intervals. Each observation is a drug-state. A drug is a competitor of a treated drug if it was not under price control but at least one drug in their ATC-4 was under price control. The policy was implemented in 2013. The standard errors are clustered at the drug level.

Figure B16: The effect of the Indian Policy on product exit



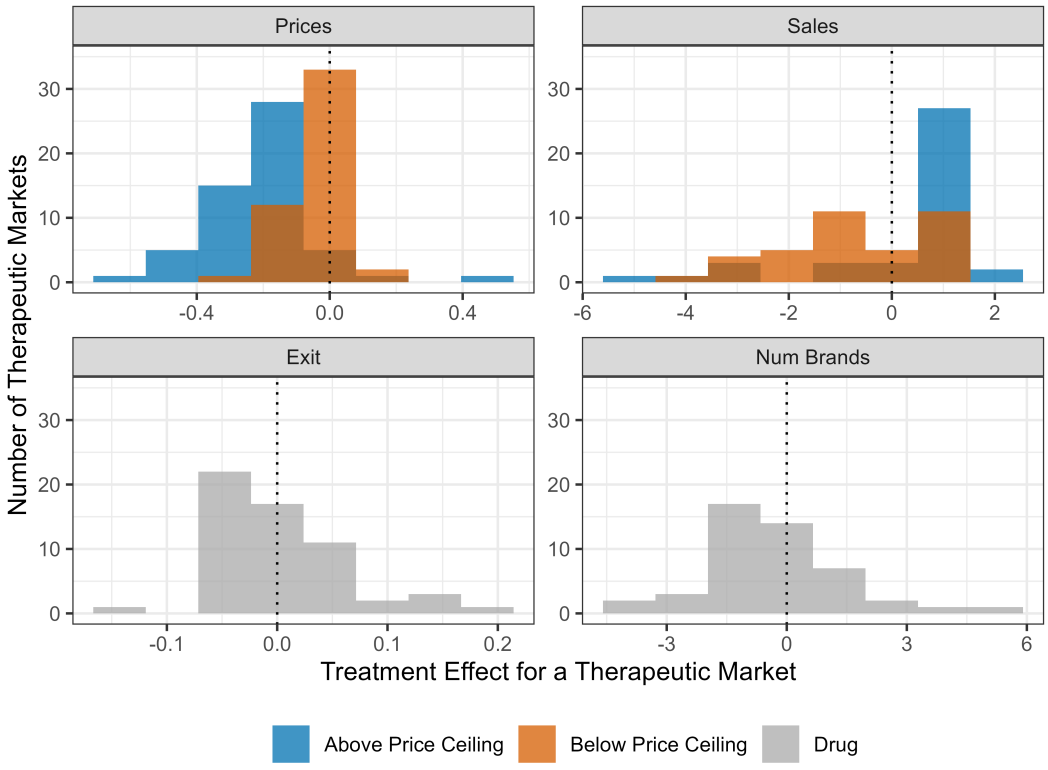
Notes: The figure presents the dynamic effects of the price control policy on the number of exits per drug. The $x-$axis is the time from when the price control was implemented (in years). The $y-$axis shows the ATT estimates with 95% confidence intervals. Each observation is a drug-state-year. A treated unit is a drug that was not under price control but at least one drug in its ATC-4 was under price control. The policy was implemented in 2013. The standard errors are clustered at the drug level.

Figure B17: The effect of the Indian Policy on new brand entry



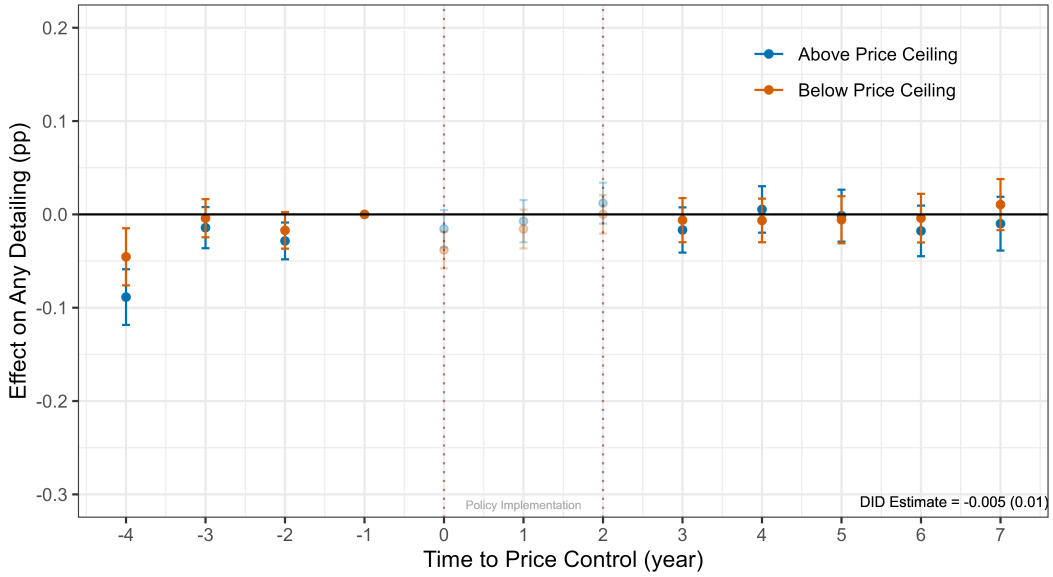
Notes: The figure presents the dynamic effects of the price control policy on whether there was a new brand entry. The $x-$axis is the time from when the price control was implemented (in years). The $y-$axis shows the ATT estimates with 95% confidence intervals. Each observation is a drug-state-year. A treated unit is a drug that was not under price control but at least one drug in its ATC-4 was under price control. The policy was implemented in 2013. The standard errors are clustered at the drug level.

Figure B18: Distribution of treatment effects across diseases



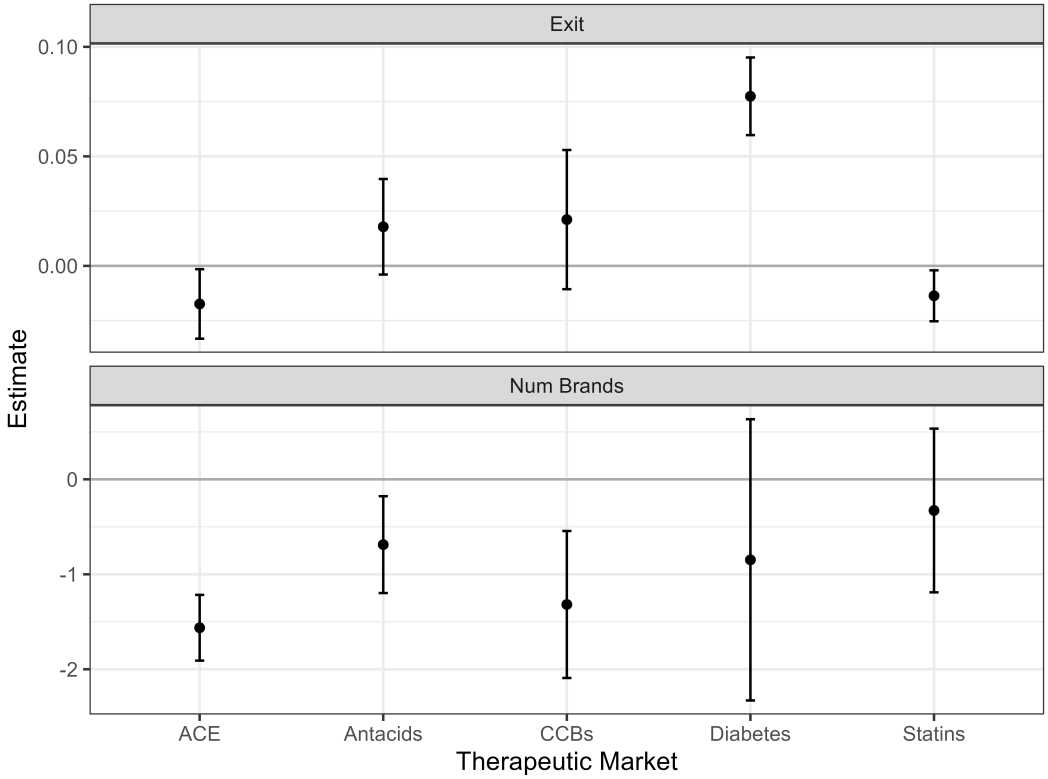
Notes: The figure presents the distribution of disease specific treatment effects on prices, sales, exit, and number of brands. The $y-$axis shows the point estimates of the ATT for a particular diseases and the $x-$axis shows the number of diseases. We exclude estimates with $p-$values exceeding 0.20.

Figure B19: The Effect of the Indian Policy on advertising to physicians (detailing) — Extensive Margin



Notes: The figure presents the dynamic effects of the price control policy on detailing at the extensive margins. The $x-$axis is the time from when the price control was implemented (in 6 months). The $y-$axis shows the ATT estimates with 95% confidence intervals. Each observation is a brand-drug. Standard errors are clustered at the brand-drug level. Estimates are presented separately for treated brand-drugs above and below the price price ceiling.

Figure B20: Distribution of treatment effects across diseases studied in the structural analysis



Notes: The figure presents therapeutic market specific treatment effects on number of exits and number of brands. The $y-$axis shows the point estimates of the ATT for a particular diseases and the $x-$axis shows the disease.

B.4 Development and Diffusion of New Molecules

B.4.1 Data and Empirical Strategy

For this analysis, we use the Pharmaprojects dataset from Pharma Intelligence, a global pharmaceutical marketing intelligence company. Pharmaprojects tracks drug development worldwide using a variety of sources and is commonly used in innovation research (Kyle, 2007; Blume-Kohout and Sood, 2013; Cunningham et al., 2021). Specifically for our purposes, Pharmaprojects records the launch of new molecules in India.

Our empirical strategy exploits differences in exposure to future price controls between firms. Drugs in certain therapeutic markets are more likely to be placed under price controls due to a higher incidence in India. For example, diabetes drugs are more likely to be regulated than mental health drugs. At the same time, different firms specialize in different therapeutic markets. For example, Merck has a strong focus on the diabetes market, while Eli Lilly is a leader in antidepressants. Based on these two features, we measure a firm's exposure to price regulations in India. Our empirical strategy compares the innovative activities of Merck-like high-risk firms with those of low-risk firms like Eli Lilly before and after the implementation of the the Indian Policy.

Formally, we measure the share of drugs e_a in the ATC-4 code a that were put under price control. We then construct a firm's portfolio across ATC-4 codes based on the number of drugs they attempted to develop n_{af} up to 2010 and measure a firm's exposure to Indian price controls as $e_f = \sum_a n_{af} e_a / \sum_a n_{af}$. In our primary analysis, we dichotomize the exposure based on a threshold: $T_f = 1\{e_f > \bar{e} = 0.3\}$. In Supplementary Figure B23, we show robustness to different thresholds $\bar{e}$. We then estimate the following regression specification:

$$Y_{ft} = \sum_k \tau_k T_f 1\{t - 2013 = k\} + \gamma_f + \alpha_{c(f)t} + \epsilon_{ft},$$

where Y_{ft} is the number of new molecules launched by firm f in year t, τ_k is the treatment effect k periods after the price control policy was implemented, γ_f is the firm fixed-effect, and $\alpha_{c(f)t}$ is the firm country-year fixed effect, where $c(f)$ firm f's home country. We cluster the standard errors at the firm level. The key identification assumption is that in the absence of the policy, high-exposure and low-exposure firms would be on parallel trends.

B.4.2 Results

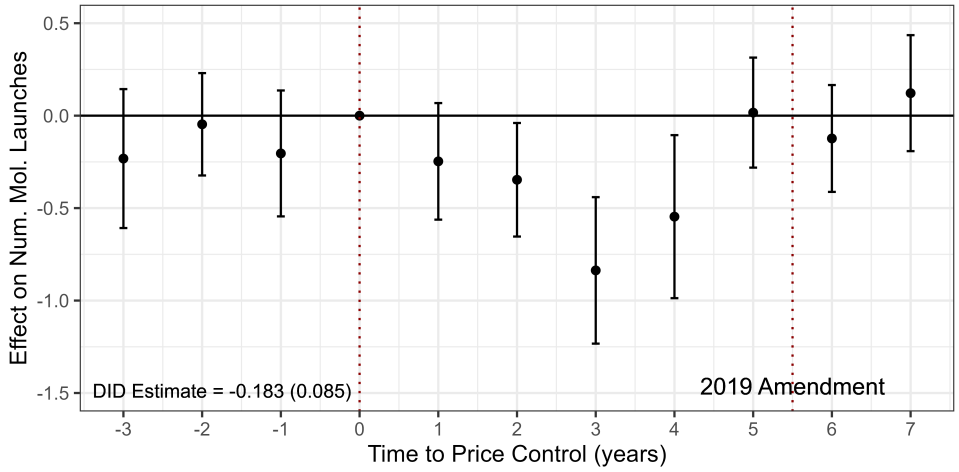
In Supplementary Figure B21, we present the estimated change in new molecules launches in India over time. We find a gradual decline in the launch of new molecules after the Indian Policy. The decline peaked in 2017 with a reduction of 0.8 new molecule launched per firm.

However, the effect appears transient and completely dissipates by 2019.

These dynamic patterns are consistent with the changes in exemptions for patented drugs. Patented drugs were not *de jure* exempted from price controls when the policy was first introduced in 2013. Subsequently, in 2017, a Supreme Court ruling limited the ability of the regulator to set the price ceiling on certain classes of patented drugs. In 2019, the Indian Policy was amended to exempt all patented drugs from price controls for a period of five years.

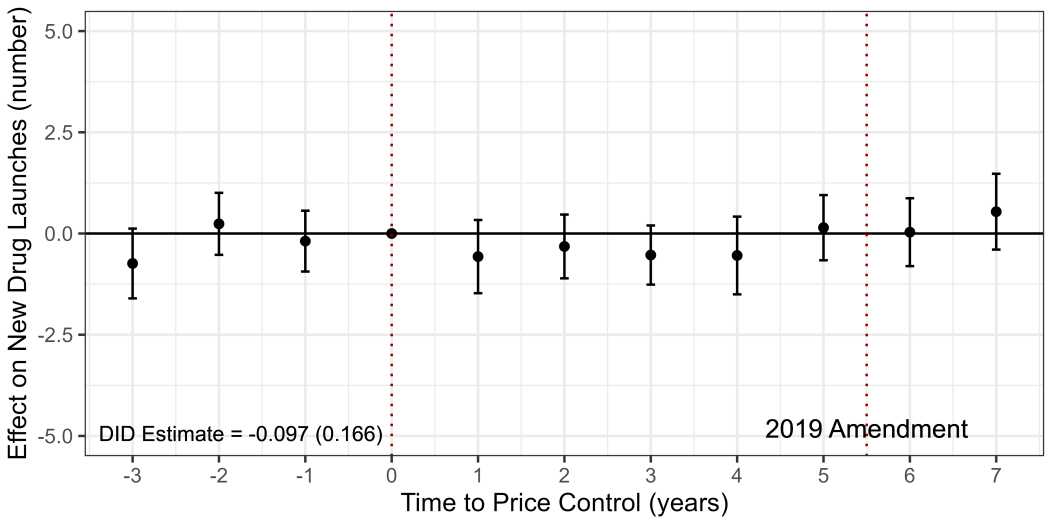
Effect on Global Innovation We also examine the effect of the Indian Policy on global drug development. In Supplementary Figures B22 and B24, we show that the Indian Policy had no economically meaningful or statistically significant impact on the launch of new molecules or new clinical trials globally. These results show that Indian price controls did not affect the output of and inputs into global biomedical innovation, which is unsurprising given that the Indian market generates a small share of global pharmaceutical revenue (IMS, 2015).

Figure B21: The Effect of the Indian Policy on new molecules launches in India



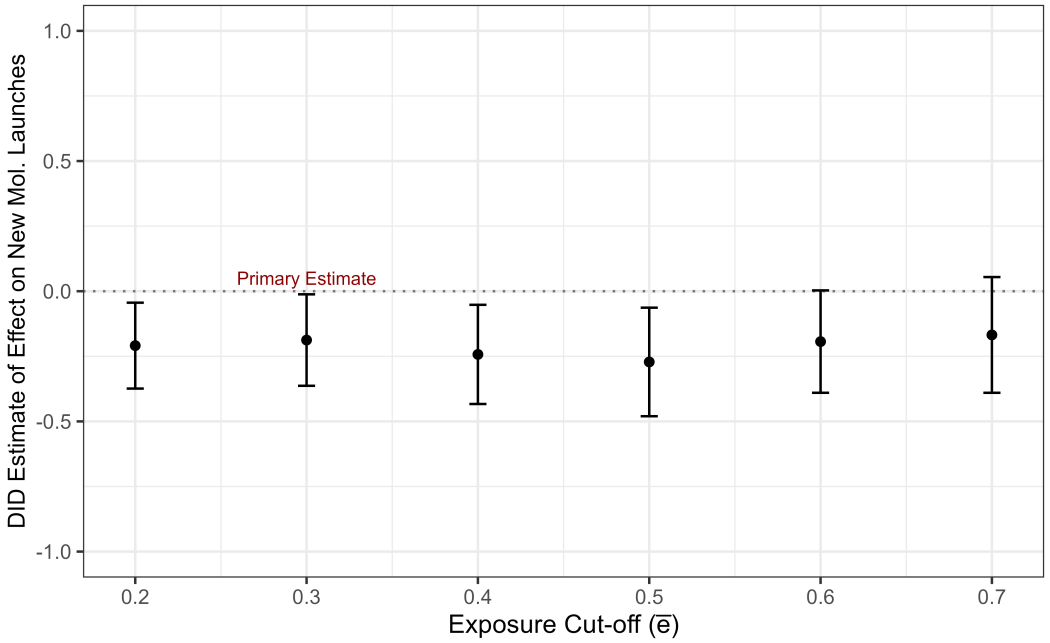
Notes: The figure presents the dynamic effects of the price control policy on the approval of new molecules in India. The $x-$axis is the time from when the price control was implemented. The $y-$axis shows the ATE estimates with 95% confidence intervals. Each observation is a firm-year pair. The standard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

Figure B22: The Effect of The Indian Policy on Approval of New Molecules Globally



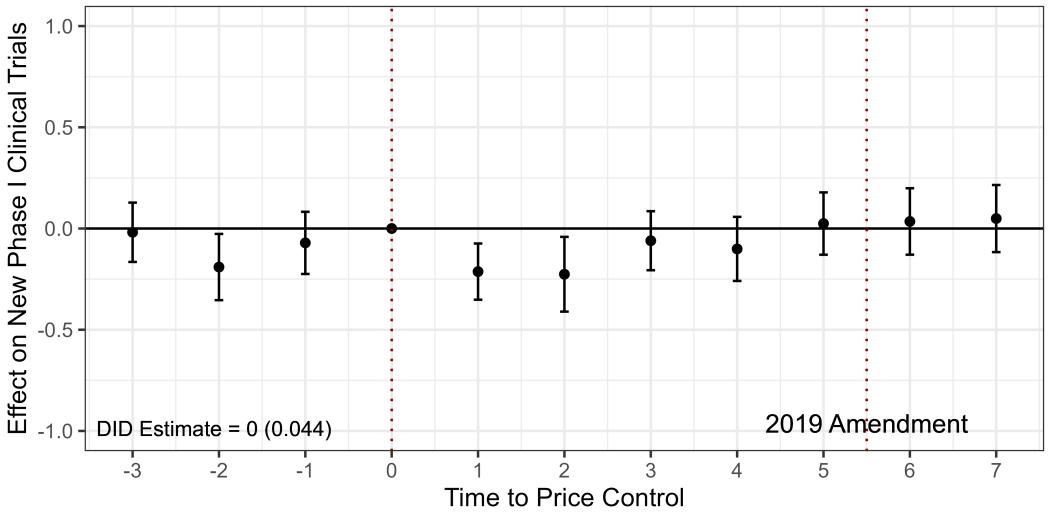
Notes: The figure presents the dynamic effects of the price control policy on the approval of new molecules globally. The $x-$axis is the time from when the price control was implemented. The $y-$axis shows the ATE estimates with 95% confidence intervals. Each observation is a firm. Standard errors are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

Figure B23: Robustness to Exposure Threshold

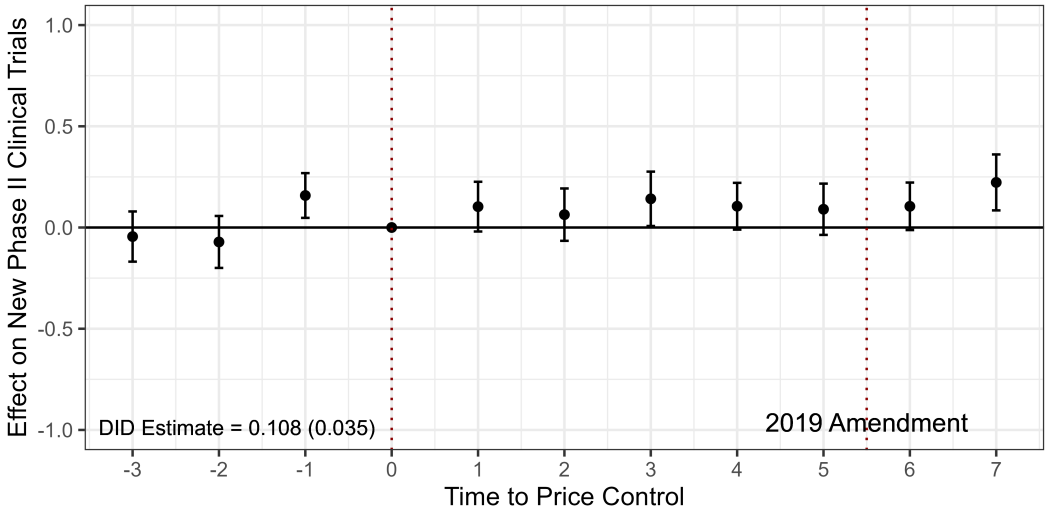


Notes: The figure difference-in-differences estimates of the price control policy on the approval of new molecules in India on the $y-$axis for different thresholds of treatment exposure cut-off $\bar{e}$ on the $x-$axis. The $y-$axis shows the ATE estimates with 95% confidence intervals. Standard errors are clustered at the firm level.

Figure B24: The Effect of the Indian Policy on Clinical Trials



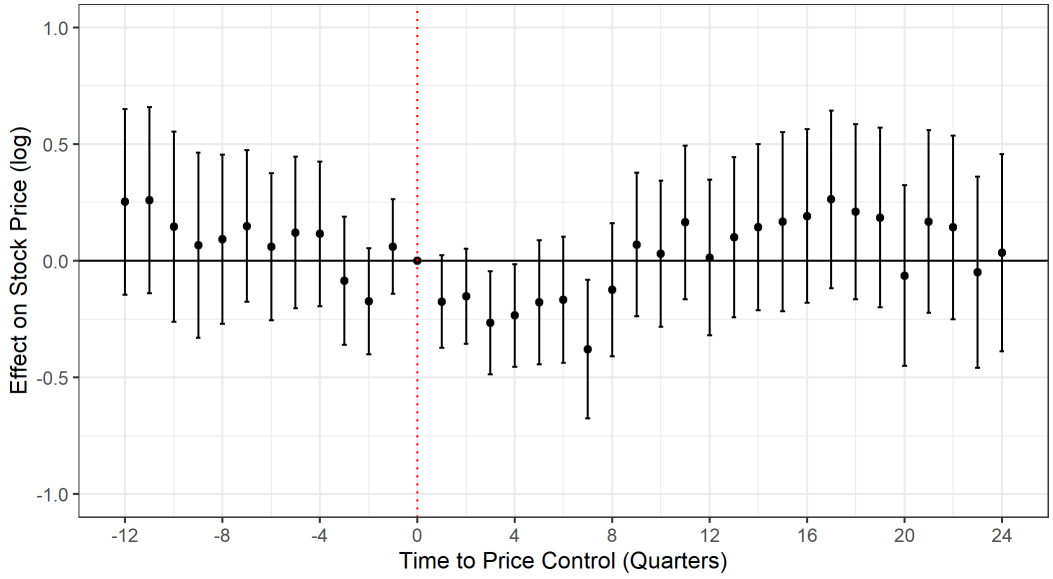
(a) Phase 1 Trials



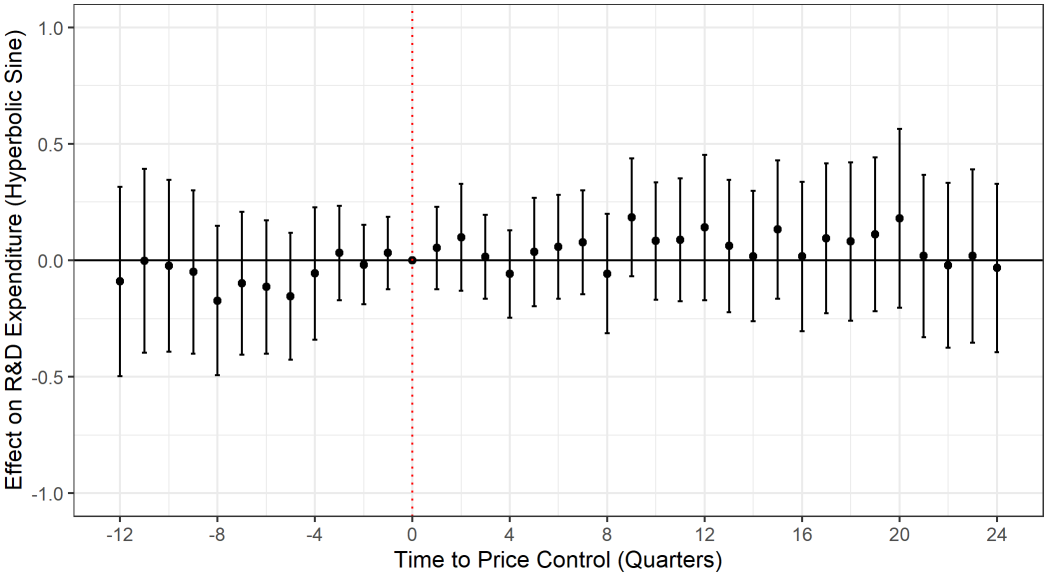
(b) Phase 2 Trials

Notes: The figure presents the dynamic effects of the price control policy on the approval of new Phase 1 (Panel A) and Phase 2 (Panel B) clinical trials. The $x-$axis is the time from when the price control was implemented in years. The $y-$axis shows the ATE estimates with 95% confidence intervals. Each observation is a firm. Standard errors are clustered at the firm level.

Figure B25: The Effect of the Indian Policy on Financial Performance of Listed Pharmaceutical Firms



(a) Stock Price



(b) Research and Development Expenditures

Notes: The figure presents the dynamic effects of the price control policy on firm stock prices (Panel A) and R&D expenditures (Panel B). The $x-$axis is the time from when the price control was implemented in quarters. The $y-$axis shows the ATE estimates with 95% confidence intervals. Each observation is a firm. The standard errors are clustered at the firm level.

C Theory Appendix

C.1 Model of Patients and Physicians

In our primary model, we consider a unitary agent representing both patients and physicians. We now present a model of patient preferences and physician prescriptions that underpins our primary model.

Similar to our primary model, we assume that there are J products. A physician can prescribe one of these products.

Patient Preferences In our primary analysis, we do not take a stand on the source of choice frictions and consider a joint decision made by physicians and patients. For illustration, we now present a microfounded model which incorporates two likely sources of frictions: mistaken beliefs among patients (characterization failure) and conflicting financial interests for physicians.

As before, a patient i's utility for product j is specified as $U_{ij}^{pat} = \delta_j - \alpha_i p_j + \epsilon_{ij}$, where $\delta_j = \delta_j^{\text{true}} + \delta_j^{\text{fr, pat}}$. If patients could choose their treatments, for example, in the case of over-the-counter drugs, they would choose $\arg\max_{j \in J} U_{ij}^{pat}$. However, for most of the treatments in our analysis, patients must obtain a prescription from a physician.

We assume that the physician knows the true quality of the product δ_j^{true}. A physician's preferences for a product depend on three components. First, the physician wants to prescribe the best treatment for their patients $\delta_j^{\text{true}} - \alpha_i p_j + \epsilon_{ij}$. Second, physicians may wish to respect patient preferences U_{ij}^{pat}. They may do so out of respect for patients or for financial reasons. For example, physicians may wish to adhere to the patient's preference so that the patient continues to visit them (Lopez et al., 2022). Third, physicians may receive direct financial incentives d_{ij} for prescribing the product j to the patient i (Iizuka, 2012; Narendran and Narendranathan, 2013). Combining these terms, a physician's utility is

$$\begin{aligned} U_{ij}^{phy} &= w^{pat}(\delta_j^{\text{true}} + \delta_j^{\text{fr,pat}} - \alpha_i p_j + \epsilon_{ij}) + (1 - w^{pat})(d_{ij} + \delta_j^{\text{true}} - \alpha_i p_j + \epsilon_{ij}) \\ &= \delta_j^{\text{true}} + \underbrace{w^{pat}\delta_j^{\text{fr,pat}} + (1 - w^{pat})d_{ij}}_{\delta_j^{\text{fr}}} - \alpha_i p_j + \epsilon_{ij}, \end{aligned}$$

where w^{pat} denotes the relative weight that a physician places on the preferences of a patient. Thus, the choice frictions in our primary model can be mapped to a model of mistaken patient beliefs, as well as wedges in the incentives of physicians and their patients. We can capture the part of the utility that captures frictions δ^{fr} without separately identifying the underlying components $w^{pat}, \delta_j^{\text{fr,pat}}, d_{ij}$.

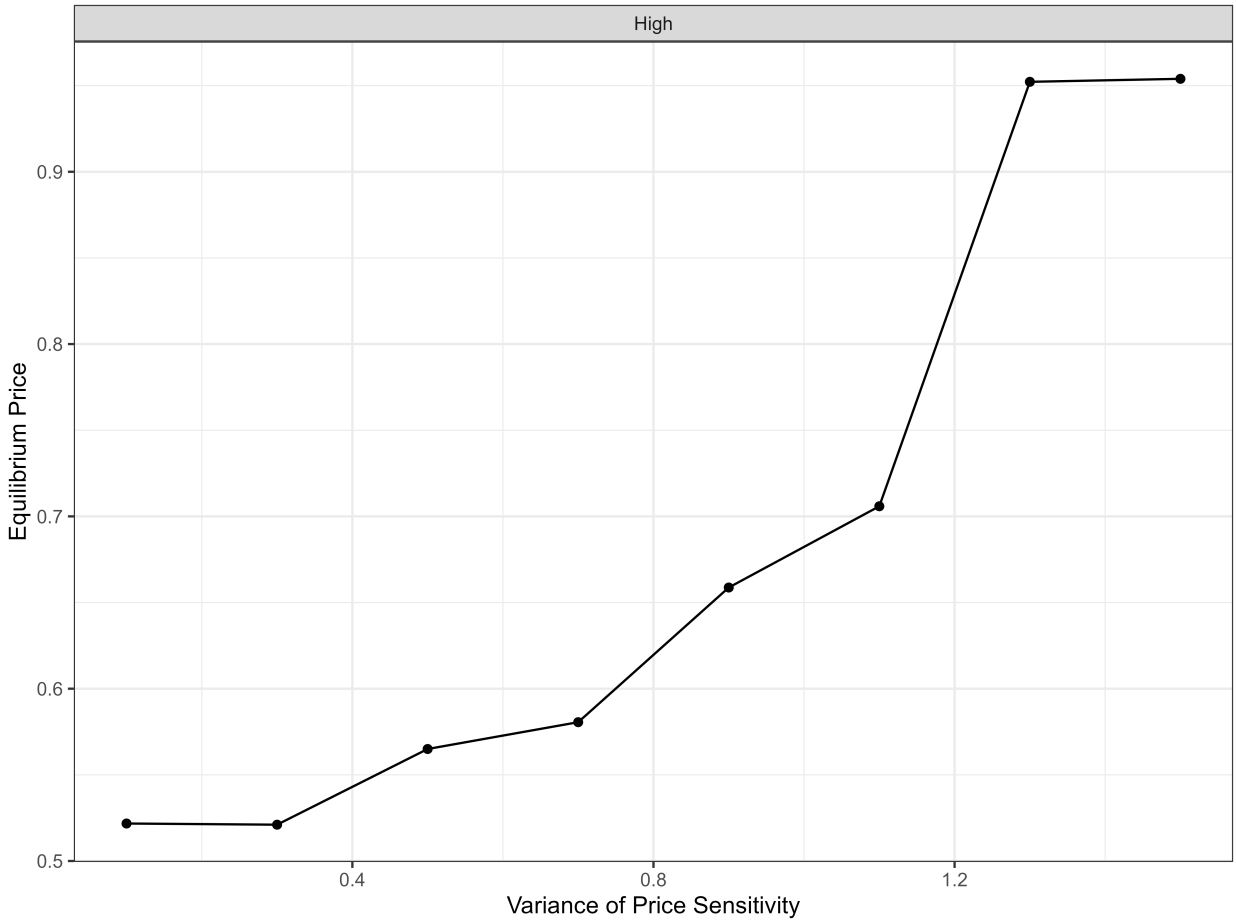
C.2 Illustration: Role of Heterogeneity in Price Sensitivity

We extend the stylized example from the main paper to illustrate how heterogeneity in consumer preferences influences market power. Recall, different consumers value two products differently because their price sensitivity may differ and because of idiosyncratic logit shocks. The ability of firms to differentiate their products then gives them market power. For example, high-quality firms may target price-insensitive consumers, and low-quality firms may target price-sensitive consumers.

To illustrate this feature, we continue with the stylized model presented earlier. We assume that $mc = 0$ for all firms, and thus, positive prices reflect markups. We assume that $\log(\alpha_i) \sim \mathcal{N}(2, \sigma^2)$. The parameter σ^2, by construction, captures the heterogeneity in consumer price sensitivity.

In Figure C1, we vary σ^2 and examine how the price of the high-quality product changes. As the variance in price sensitivity increases, the price of the high-quality product increases. As the degree of perceived product differentiation increases, keeping the mean price sensitivity fixed, firms are able to charge higher markups.

Figure C1: Relationship between price of high-quality product and the variance in consumer price sensitivity



Notes: The figures present equilibrium price of the high-quality product p_h and the variance in consumer price sensitivity.

C.3 Microfoundation of Utility Specification

We provide a microfoundation for the utility specification in our model. Consumers derive utility $U_i(\delta, c)$ from health δ and non-health consumption c. A consumer is endowed with income y_i and chooses a product $j \in J$. For a given product j, a consumer receives health benefits δ_{ij} but must pay a price p_j and thus reduce their non-health consumption $c = y_i - p_j$.

Consumers choose a single product that maximizes their utility:

$$\max_{j \in J} U_i(\delta_{ij}, y_i - p_j)\,. \tag{C.1}$$

We first assume the following Cobb-Douglas utility specification:

$$U_{ij} = (y_i - p_j)^{\alpha_{\theta_i}} \exp(\delta_{ij})\,.$$

We then make two key assumptions. First, we assume that the relative preferences of the consumer for residual income and health utility depend only on their health status θ_i. Second, we assume that the heterogeneity in the perceived utility of the product depends on the average treatment effect of the product and idiosyncratic shocks: $\delta_{ij} = \delta_j + \zeta_{im(j)} + (1-\rho)\,\epsilon_{ij}$. The term δ_j is the average treatment effect of the product, $\zeta_{im(j)}$ captures the effects of the match of a molecule with the consumer i, and ϵ_{ij} are idiosyncratic errors that affect the benefits of the individual.

Finally, we take logs of the cobb-douglas utility function and then take a first-order Taylor expansion to yield the utility specification used in our main analysis. Because this is a monotonic transformation, it leaves the choice behavior unchanged. The final utility specification is $U_{ij} = \delta_j + \zeta_{im(j)} + (1-\rho)\,\epsilon_{ij} - \alpha_i p_j$, where $\alpha_i = \alpha_{\theta_i}/y_i$. We perform this transformation to simplify the computation.

Our utility specification is similar to those commonly used in industrial organizations such as Berry et al. (1995) and in health economics such as Finkelstein et al. (2019).

D Review of Literature on Brand Quality

Academic Literature We begin by examining the existing literature on brand quality. Bate et al. (2011) and Bate et al. (2016) study 200 and 1470 product samples manufactured in India, respectively, and find that approximately 10% of them are substandard. In most cases, these drugs are substandard as they contain lower amounts of the active ingredient. Bennett and Yin (2019) find that 93% of the samples of two popular antibiotics are standard. Ozawa et al. (2018) perform a meta-review of this literature and confirm that, in India, the rates of substandard medications are generally less than 10% across all studies and in almost all cases the drugs are substandard due to lower amounts of active ingredient.

None of the studies find spurious drugs or other major defects with different brands of the same drug.

A major limitation of the academic literature is that most papers focus on 2-3 molecules, sample in one geographic region, focus on popular brands, and have sample sizes ranging from $100 - 1000$ samples. In fact, Ozawa et al. (2018) document that across all 40 studies conducted in Asia (not just India) there are $17,928$ samples collected. This represents a small share of the market, making it difficult to generalize these findings. In addition, these studies mainly include popular brands and do not provide information on quality by brand. Consequently, they are of limited use to learn about the differences in quality between a wide array of brands, which is central to our particular question.

Government Inspections The Central Drugs Standard Control Organisation (CDSCO) is required to make annual reports to the Indian government on the quality of drugs on the market.[1] To this end, CDSCO performs large-scale inspections that include more than $32,770$ samples across multiple drugs and regions in India.

These inspections report that the rates of substandard drugs were approximately 10% in the 1990s and have been steadily declining. For inspections performed after 2014 the rates of substandard drugs are less than 4%. The rates of spurious drugs have never exceeded 0.5% (Singh et al., 2020).

Note that government reports find much lower rates of substandard drugs compared to academic literature. Despite the comprehensive nature of these inspections, researchers and public health experts have expressed concerns about the quality of data collection and the accuracy of the reporting, limiting our ability to draw firm conclusions.

[1] Roughly speaking, the CDSCO is the analog of the FDA in the US.

E Survey

E.1 Robustness and Validation

We evaluate differences in choices by proxies of physician knowledge with the following regression.

$$Y_i = \beta X_i + \epsilon_i \,, \tag{E.1}$$

where X_i represent physician characteristic. Y_i is an indicator for whether a physician chooses a brand that was above the price ceiling and, in a separate regression, an indicator for whether a physician chooses a multinational brands. The results are presented in Tables E2 and E3. We find little meaningful or statistically significant correlation between proxies of physicians knowledge and their choices.

E.1.1 Patient and Pharmacist Survey

We conducted a patient survey to descriptively compare how brand choices vary with employment status, education, sex, and location of consumers. In addition, we conducted a survey of pharmacists to examine how choice vary with proxies of pharmacist knowledge.

In collaboration with the Abdul Latif Jameel Poverty Action Lab (J-PAL), we conducted in-person surveys in Bengaluru and Delhi from June 5th, 2024 to July 9th, 2024. We focused on urban areas to ensure that we can recruit participants who are educated and employed. The survey recruited participants who had Diabetes, Acid Reflux, or Cardiovascular diseases. Our sample consists of 267 patients and 60 pharmacists.

Our survey collected the demographics of the patient: income, education, employment, occupation industry, sex, and location. In Table E4, we present the descriptive statistics of these variables. For pharmacists, we also collected information on whether they own the pharmacy, whether they were formally trained as a pharmacist, how long they have worked as a pharmacist, and the number of customers they see each week. See Table E5 for key descriptive statistics.

We record the molecules and brands that consumers took for their own treatment. To ensure accuracy, surveyors verified responses by checking the prescription or the medicine itself. We also asked qualitative questions to determine the rationale behind consumer choices and preferences. A copy of the survey in English is attached.

We evaluated the differences in choices by different characteristics with the following regression.

$$Y_i = \beta X_i + \epsilon_i \,, \tag{E.2}$$

where X_i represent repsondent characteristics. Y_i is an indicator for whether a respondent chooses a brand that was above the price ceiling. The results are presented in Table E6 and Table E7.

We find that, conditional on income, the choices of patients do not systematically vary with education, occupation, or sex. These demographic characteristics explain very little of the variation in choices. We find that patients who can accurately describe a generic drug are less likely to buy expensive brands, although this difference is statistically imprecise.

Similarly, we find that the choices of pharmacists do not vary by age and sex. However, we find that pharmacists who report having received formal training and who have been pharmacists for more than a year are less likely to buy expensive brands. These findings suggest that pharmacists who are more knowledgeable are less likely to buy expensive brands, further supporting our result that brand preferences likely reflect incomplete information (and not differences in preferences).

E.2 Figures and Tables

Table E1: Characteristics of physician sample

Characteristic	**N = 617**
N	617
Age	28 (25, 36)
Sex	
Female	37% (228)
Male	63% (389)
Monthly Exp.	
Less than Rs. 100	0.8% (5)
Rs 100 to Rs 500	0.8% (5)
Rs 500 to Rs 1,500	1.8% (11)
Rs. 1,500 to Rs 3,000	5.3% (33)
Rs 3,000 to Rs 7,500	15% (94)
Rs 7,500 to Rs 15,000	27% (169)
Rs 15,000 to Rs 50,000	36% (224)
More than Rs 50,000	12% (76)
Type	
General Physician	69% (427)
Specialist	31% (190)
Post-Graduate Degree	36% (225)
Practice Type	
Nursing Home	3.1% (19)
Other	12% (72)
Private clinic	14% (87)
Private hospital	30% (188)
Public health center	13% (78)
Public hospital	28% (173)
Hours Practice (per week)	
Less than 20 hours	11% (66)
20 to 40 hours	18% (114)
40 to 60 hours	49% (304)
60 to 100 hours	19% (116)
More than 100 hours	2.8% (17)
Knowledge Score	
0	36% (220)
1	50% (306)
2	15% (91)
Disease	
ACE Inhibitors for Hypertension	20% (123)
Acid reducers for GERD (acid reflux)	35% (214)
Blood glucose lowering drugs for Diabetes	12% (71)
Calcium Channel Blockers for Hypertension	18% (111)
Statins for High Cholesterol	16% (98)

Table E2: Relationship between physician characteristics and baseline choices: multinational brands

	Buy Multinational Brand					
	(1)	(2)	(3)	(4)	(5)	(6)
Log (Income)	0.0026					0.0018
	(0.0039)					(0.0037)
Has Disease		-0.0118				-0.0119
		(0.0120)				(0.0112)
Is Specialist			0.0009			-0.0085
			(0.0095)			(0.0284)
Post Grad.				0.0086		0.0162
				(0.0121)		(0.0290)
Correct Knowledge Check					0.0178	0.0159
					(0.0119)	(0.0128)
Within R^2	0.00048	0.00134	6.77×10^{-6}	0.00063	0.00274	0.00527
state fixed effects	✓	✓	✓	✓	✓	✓

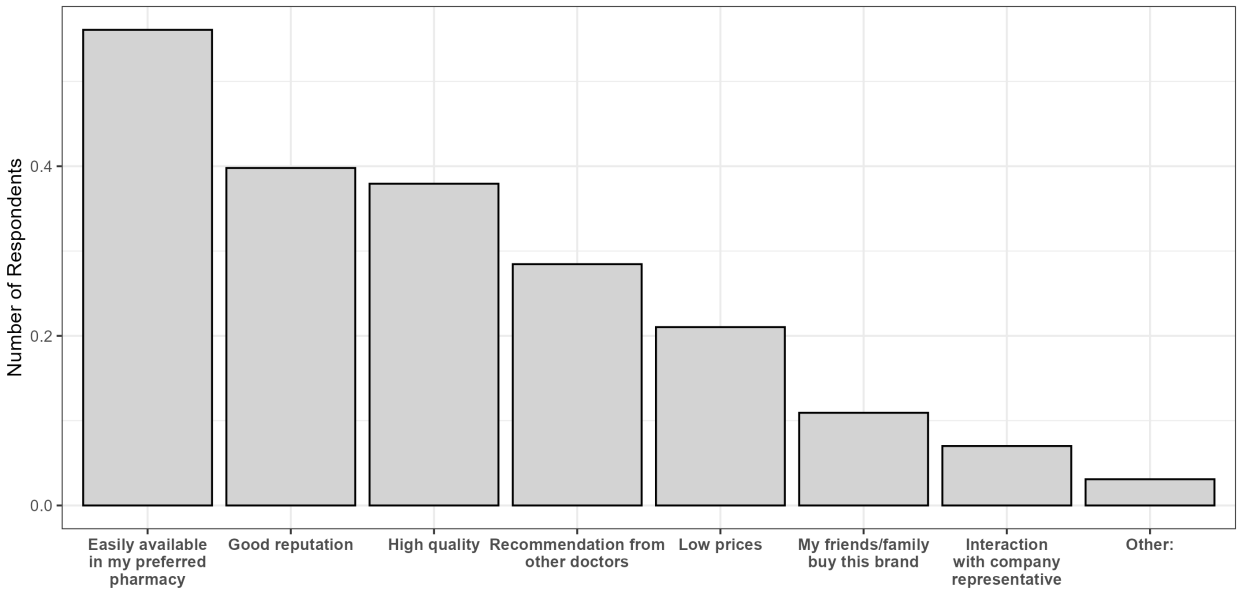
Notes: The table presents the estimates of the univariate regression specified in Equation E.1 for different characteristics X_i. The dependent variable is an indicator for whether physician i bought a multinational brand for their own treatment.

Table E3: Relationship between physician characteristics and baseline choices: high-priced brands

	Buy High Priced Brand					
	(1)	(2)	(3)	(4)	(5)	(6)
Log (Income)	-0.0073					-0.0097
	(0.0138)					(0.0126)
Has Disease		0.0466*				0.0344
		(0.0256)				(0.0316)
Is Specialist			0.0424			-0.0076
			(0.0514)			(0.0529)
Post Grad.				0.0507		0.0529
				(0.0461)		(0.0467)
Correct Knowledge Check					-0.0700	-0.0634
					(0.0788)	(0.0843)
Within R^2	0.00044	0.00247	0.00162	0.00261	0.00502	0.00939
state fixed effects	✓	✓	✓	✓	✓	✓

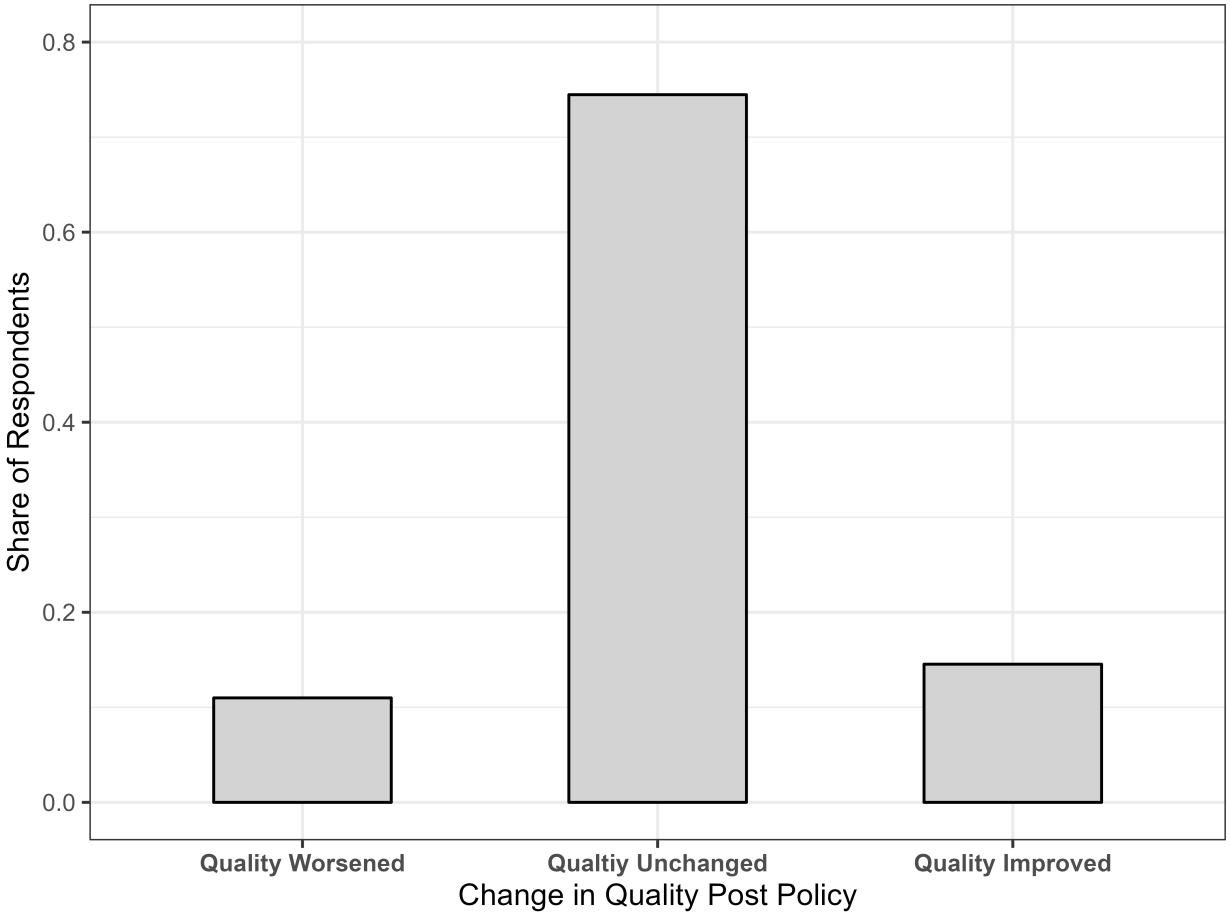
Notes: The table presents the estimates of the univariate regression specified in Equation E.1 for different characteristics X_i. The dependent variable is an indicator for whether physician i bought a brand that was above the price ceiling for their own treatment.

Figure E1: Rationale for choice



Notes: The figure presents the rationale that physicians select for their choices. Physicians are allowed to select multiple rationales

Figure E2: Physician perceptions of change in product quality



Notes: The figure presents the share of physicians who believe that quality of their chosen brand has improved, gotten worse, or remained the same after the the Indian Policy.

Table E4: Characteristics of Patient Sample

Characteristic	**N = 267**
Location	
Delhi	18% (49)
Karnataka	82% (218)
Age	60 (53, 69)
Sex	
Female	56% (149)
Male	44% (118)
Education	
No Education	10% (28)
Primary	2.2% (6)
Secondary	9.0% (24)
10th Grade	21% (57)
High School	16% (43)
Some College	2.6% (7)
Diploma	2.6% (7)
Bacherlor's	28% (75)
Post Grad	7.5% (20)
Annual Income (Rs.)	
< 50,000	3.8% (10)
50,000 - 100,000	3.1% (8)
100,000 - 500,000	14% (37)
500,000 - 1,000,000	42% (109)
1,000,000 - 2,500,000	18% (47)
> 2,500,000	0% (0)
Refused	19% (49)
Healthcare Employee	6

Table E5: Characteristics of Pharmacist Sample

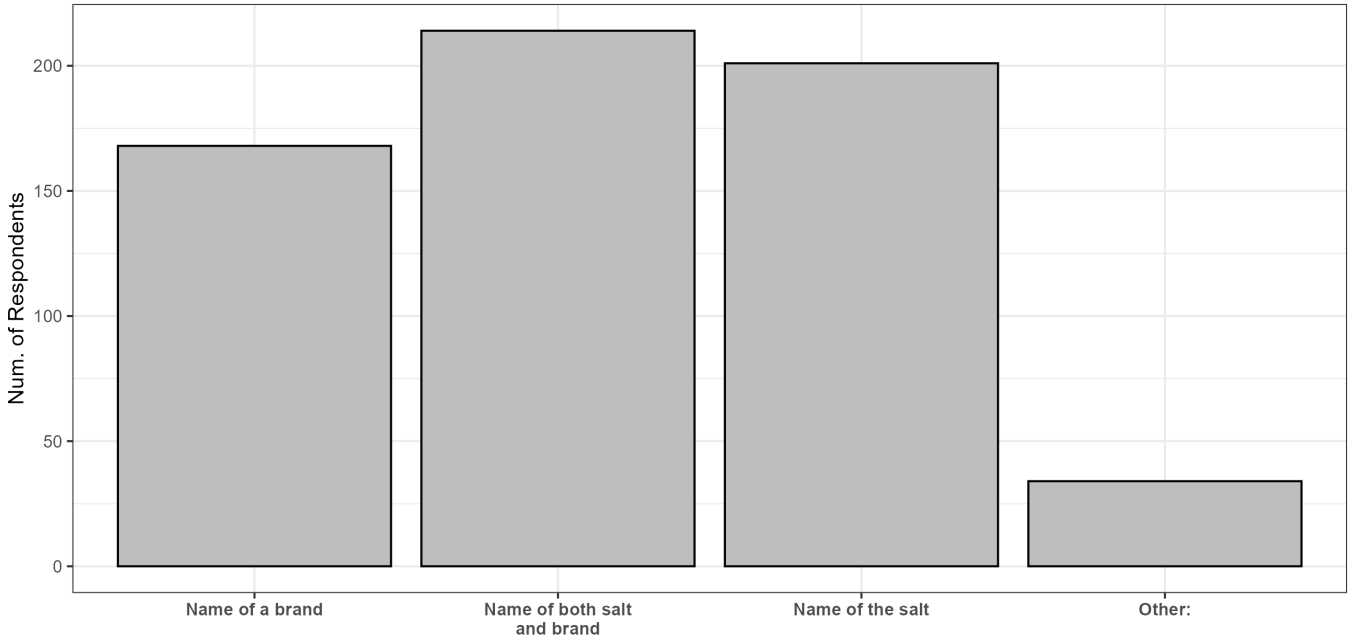
Characteristic	**N = 60**
Location	
Delhi	20%
Karnataka	80%
Age	32 (26, 43)
Sex	
Female	22%
Male	78%
Annual Income (Rs.)	
< 50,000	0%
50,000 - 100,000	0%
100,000 - 500,000	18%
500,000 - 1,000,000	45%
1,000,000 - 2,500,000	22%
> 2,500,000	0%
Refused	15%
Own Pharmacy	48%
Pharmacy Education	70%
Experience (years)	6 (4, 15)
Customers (per week)	325 (151, 647)

Table E6: Relationship Between Patient Characteristics and Choosing a High Priced Brands

	Buy High Priced Brand						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Male	0.0371			0.0939			0.1278
	(0.0834)			(0.1622)			(0.1680)
Self-employed		0.1682		0.1183			0.0789
		(0.1525)		(0.2038)			(0.2055)
Employed		-0.1652		-0.1556			-0.2452
		(0.1472)		(0.2247)			(0.2281)
Gov. Employee		0.0767		0.0608			0.0701
		(0.1618)		(0.2269)			(0.2347)
Retired		-0.1179		-0.1905			-0.2599
		(0.1112)		(0.1688)			(0.1741)
Other		-0.1430		-0.1561			-0.1591
		(0.1442)		(0.1514)			(0.1506)
Primary Educ.			-0.2909	-0.3129		-0.2901	-0.3047
			(0.4638)	(0.4654)		(0.4630)	(0.4610)
Secondary Educ.			-0.0613	-0.1272		-0.0296	-0.1086
			(0.1903)	(0.1932)		(0.1945)	(0.1967)
10th Grade			-0.1502	-0.2211		-0.1447	-0.2215
			(0.1755)	(0.1794)		(0.1751)	(0.1778)
High School			-0.1290	-0.2031		-0.1412	-0.2108
			(0.1784)	(0.1890)		(0.1811)	(0.1888)
Some College			-0.1017	-0.0292		-0.0831	0.0434
			(0.2939)	(0.3222)		(0.2943)	(0.3211)
Diploma			-0.4910*	-0.5461*		-0.4842*	-0.5012*
			(0.2491)	(0.2821)		(0.2487)	(0.2810)
Bachelor's Degree			-0.0558	-0.1068		-0.0396	-0.0663
			(0.1673)	(0.1784)		(0.1685)	(0.1797)
Post-Grad Degree			0.0132	-0.0744		0.0560	0.0124
			(0.2114)	(0.2283)		(0.2145)	(0.2313)
Knows Generic Meds					-0.0530	-0.0639	-0.1131
					(0.0882)	(0.0948)	(0.1013)
Within R^2	0.00144	0.04154	0.04167	0.08933	0.00267	0.05014	0.11265
State fixed effects	✓	✓	✓	✓	✓	✓	✓
Income fixed effects	✓	✓	✓	✓	✓	✓	✓

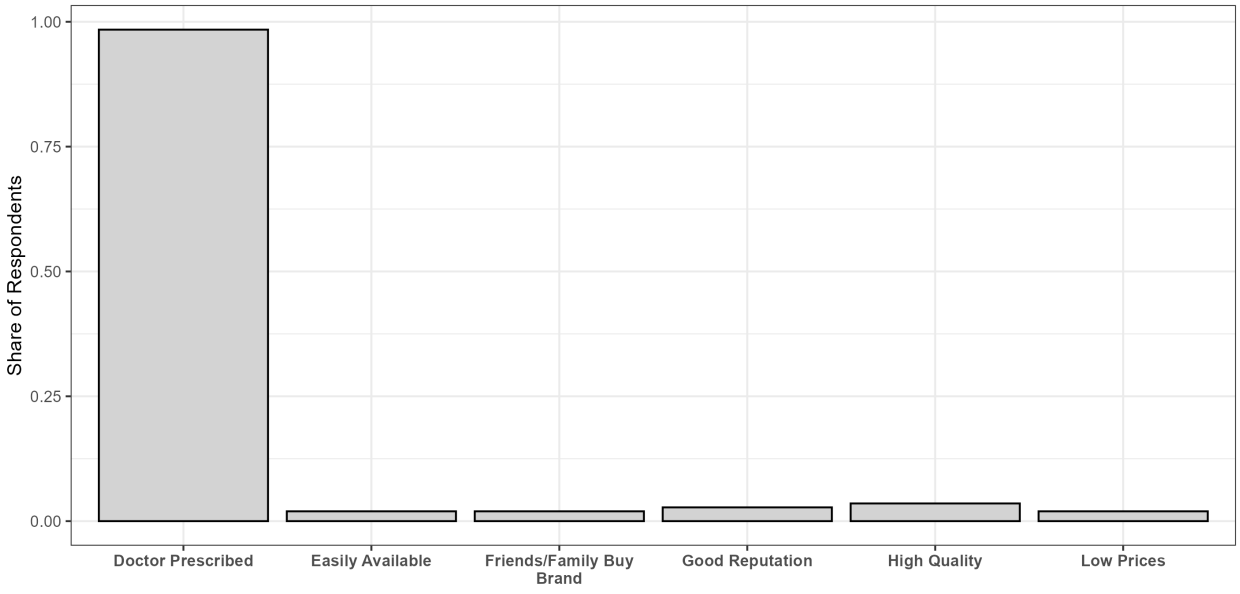
Notes: The table presents the estimates of the regression specified in Equation E.2 for different characteristics X_i. The dependent variable is an indicator for whether participant i bought a brand that was above the price ceiling for their own treatment.

Figure E3: Physician prescription patterns



Notes: The figure present the share of physicians who write a brand name or molecule name in their prescriptions.

Figure E4: Patient Rationale for Brand Choice



Notes: The figure presents the rationale for choosing a given brand on the $x-$axis and the share of participants that report the corresponding rationale on the $y-$axis.

Table E7: Relationship Between Pharmacist Characteristics and Choosing a High Priced Brands

	Buy High Priced Brand							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	0.0129**		0.0136**					
	(0.0060)		(0.0060)					
Male		0.1932	0.2277					
		(0.1757)	(0.1699)					
Own Pharmacy				0.2852*				0.3057*
				(0.1437)				(0.1583)
Has Pharmacist Education					-0.1594			-0.2119
					(0.1596)			(0.1587)
Pharmacist for >1 year						-0.2991		-0.4186*
						(0.2363)		(0.2414)
Customers (per week, log)							-0.0719	0.0107
							(0.0758)	(0.0805)
Within R^2	0.07997	0.02230	0.11069	0.06922	0.01849	0.02933	0.01698	0.14208
State fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Income fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents the estimates of the regression specified in Equation E.2 for different characteristics X_i. The dependent variable is an indicator for whether participant i bought a brand that was above the price ceiling for their own treatment.

F Structural Analysis

F.1 Market Selection Criteria

We selected therapeutic markets based on two criteria. First, the therapeutic category must have at least two molecules in at least half of the states of India. This criterion ensures that the markets have enough products to provide us with a reasonable sample size. In our sample, 30 therapeutic categories satisfy this criterion.

Our second criterion is that the market must be regulated by the the Indian Policy. We require that the market has at least one regulated molecule with at least two products that are above the price ceiling. We impose this restriction to ensure that our instruments would generate variation in prices. After this filter, 25 markets remain.

We then excluded markets based on qualitative factors. First, we excluded mental health markets and "sensory organ" markets because they are quite small. We also excluded the market for anti-infectives as they are typically used for multiple diseases, which creates ambiguity in the market definition. We excluded markets where the products are topically applied (eg., dematological markets) and where the products are taken in inpatient settings (eg., antineoplatic markets).

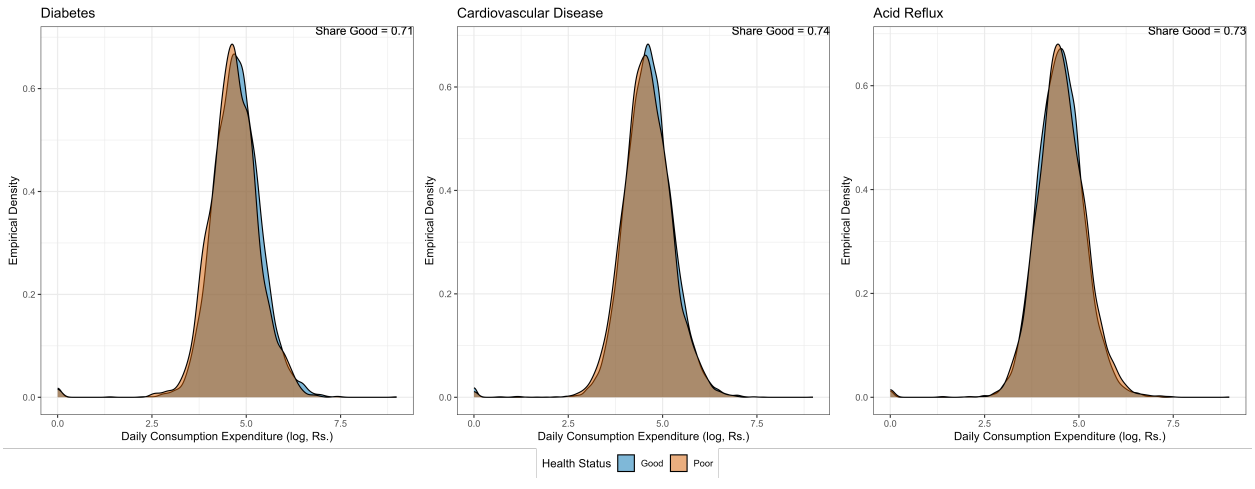
The descriptive statistics of the 5 markets in our sample are presented in Table F1.

Table F1: Descriptive Statistics of Markets

Statistic	ACE	Antacids	CCBs	Diabetes	Statins
Num. Products					
Median	86.50	100.50	79.00	223.00	149.00
Min - Max	68.00 - 101.00	86.00 - 118.00	68.00 - 86.00	203.00 - 257.00	132.00 - 175.00
Num. Mols					
Median	4.00	7.00	5.00	11.00	5.00
Min - Max	4.00 - 4.00	7.00 - 7.00	5.00 - 5.00	10.00 - 11.00	5.00 - 5.00
Num. Firms					
Median	23.50	36.50	24.00	43.00	33.00
Min - Max	18.00 - 27.00	33.00 - 43.00	20.00 - 28.00	37.00 - 49.00	27.00 - 39.00
Average Annual Expenditure					
Median	27.23	10.33	17.19	42.17	54.94
Min - Max	24.22 - 30.46	7.71 - 15.95	14.04 - 21.09	35.02 - 58.92	44.24 - 61.48
Num. Price Controlled					
Median	38.00	39.00	58.00	63.50	51.00
Min - Max	29.00 - 43.00	31.00 - 49.00	46.00 - 67.00	57.00 - 80.00	41.00 - 59.00
Market Size (millions)					
Median	0.13	1.19	0.31	0.26	0.20
Min - Max	0.02 - 0.35	0.54 - 4.62	0.14 - 1.38	0.07 - 0.91	0.05 - 0.86
Share Inside					
Median	0.82	0.73	0.58	0.70	0.55
Min - Max	0.54 - 0.91	0.40 - 0.91	0.43 - 0.83	0.51 - 0.89	0.41 - 0.76

F.2 Descriptive Results

Figure F1: Distribution of Income and Health Status



Notes: The figure presents the empirical distribution of log daily consumption expenditure by health status for different diseases.

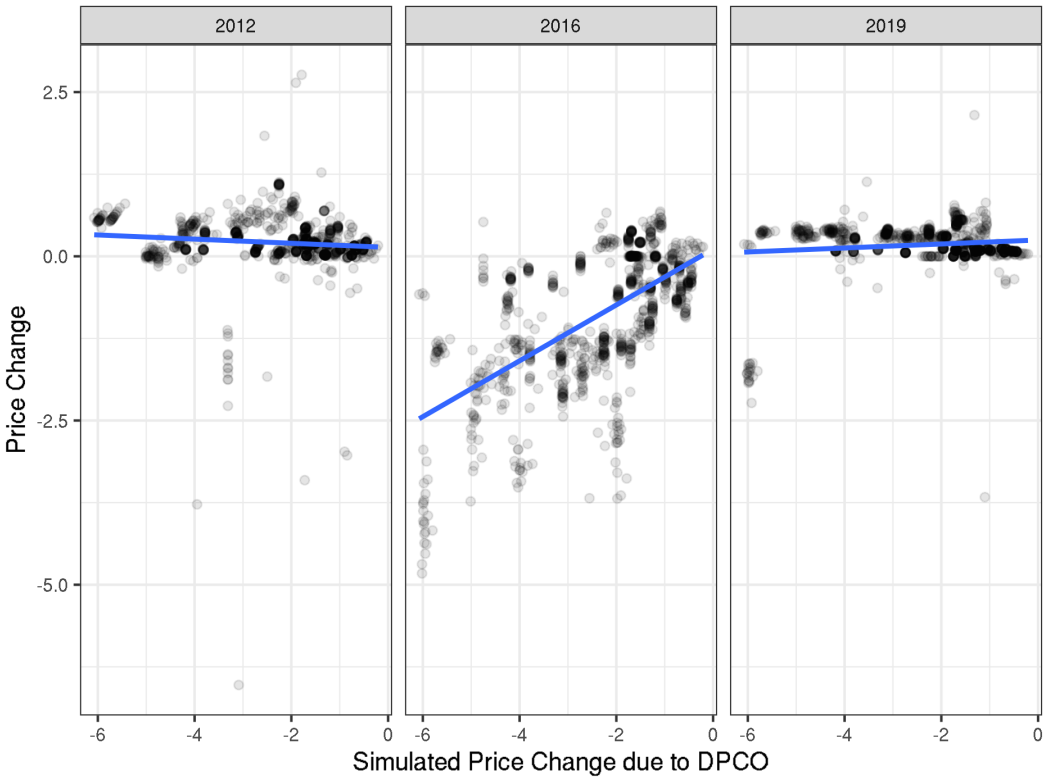
Table F2: Regression Estimates of Instruments on Prices (First Stage)

	Price Change				
	Antacids	Diabetes	Calcium Channel	ACE	Statins
	(1)	(2)	(3)	(4)	(5)
Own Price Change	-0.9905***	-1.014***	-0.6796***	-0.6291***	-0.8673***
	(0.0835)	(0.0246)	(0.0242)	(0.0336)	(0.0164)
Other Brand Price Change × group = AvgPriced	-0.4230***	0.1740*	0.7012***	-2.062***	-2.142***
	(0.0716)	(0.0887)	(0.0679)	(0.1407)	(0.1330)
Other Brand Price Change × group = HighPriced	-0.3629***	0.3322***	1.711***	-2.022***	-2.213***
	(0.1176)	(0.0872)	(0.1161)	(0.1606)	(0.1821)
Other Brand Price Change × group = LowPriced	-0.3516***	-0.2090**	0.2107**	-1.918***	-1.462***
	(0.1008)	(0.0988)	(0.0851)	(0.1662)	(0.1455)
Other Mol. Price Change	-3.374***	0.6521**	-0.7027***	-2.173***	-1.377***
	(0.2359)	(0.2771)	(0.1672)	(0.1692)	(0.1480)
Within R^2	0.19776	0.07963	0.50616	0.10598	0.15271
Wald (joint nullity)	120.56	487.62	270.29	136.17	1,057.4
F-test (projected), stat.	411.46	335.13	1,388.4	155.96	468.21
Year - G_{js} fixed effects	✓	✓	✓	✓	✓
year-State fixed effects	✓	✓	✓	✓	✓

Table F3: Regression Estimates of Instruments on Shares (Reduced Form)

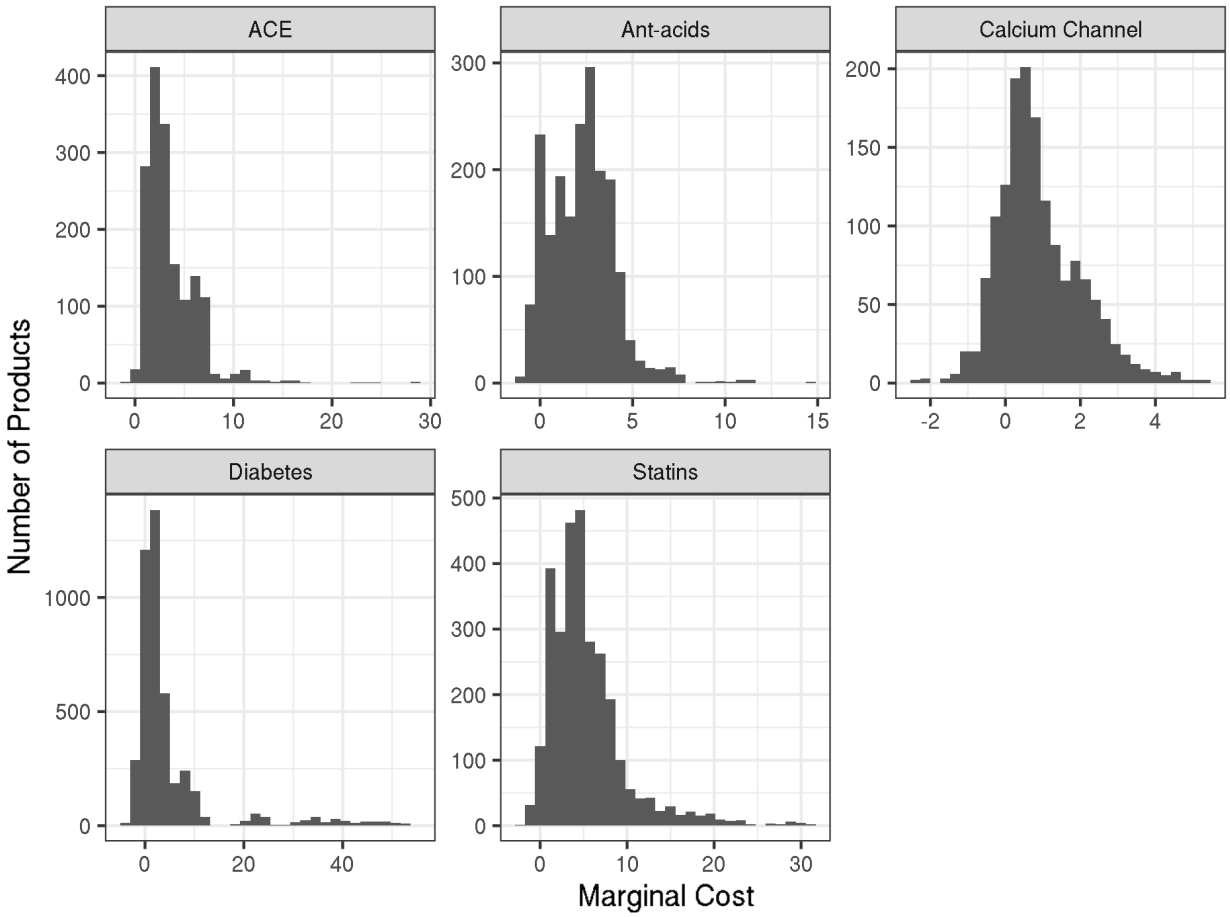
	Market Share Change				
	Antacids	Diabetes	Calcium Channel	ACE	Statins
	(1)	(2)	(3)	(4)	(5)
Own Price Change	-0.0192	0.0881***	0.1038**	0.2534***	0.0102
	(0.0804)	(0.0194)	(0.0448)	(0.0679)	(0.0178)
Other Brand Price Change × group = AvgPriced	-0.1251	0.3296*	0.2242**	-0.0372	1.489***
	(0.0921)	(0.1740)	(0.1064)	(0.3360)	(0.2058)
Other Brand Price Change × group = HighPriced	0.0195	0.1250	0.1540	0.4139	1.364***
	(0.1065)	(0.1728)	(0.1610)	(0.3399)	(0.2139)
Other Brand Price Change × group = LowPriced	-0.9479***	0.3768*	-0.0974	-0.4605	1.309***
	(0.2897)	(0.1908)	(0.1181)	(0.4003)	(0.2509)
Other Mol. Price Change	-0.4254	0.4965	0.3010	-0.2436	1.746***
	(0.2555)	(0.5181)	(0.2590)	(0.3833)	(0.2429)
Within R^2	0.01683	0.00575	0.00688	0.01315	0.05547
Wald (joint nullity)	2.5885	12.914	3.4892	5.2317	18.649
F-test (projected), stat.	28.569	22.403	9.3806	17.529	152.56
Year - G_{js} fixed effects	✓	✓	✓	✓	✓
year-State fixed effects	✓	✓	✓	✓	✓

Figure F2: Correlation Between Observed Price Changes and Simulated Price Changes



Notes: The figure presents the correlation between the observed year-over-year price changes and the simulated reduction in prices E_{js} for three years.

Figure F3: Distribution of Marginal Costs in 2013



Notes: The figure presents the distribution of marginal costs mc_{jst} in 2013 for different diseases.

F.3 Relationship between moments and parameters

We heuristically discuss how different parameters are related to moments using an illustrative example. Consider a market with 3 products $j \in \{H, M, L, 0\}$ with pre-policy prices $p_H = 6, p_M = 2, p_L = 1, p_0 = 0$ and shares $s_H = 0.6, s_M = 0.15, s_L = 0.15, s_0 = 0.1$. In this example, the the Indian Policy would result in a price ceiling $\bar{p} = 3$, which would be binding only for H and would result in a price change of $\Delta p_H = 3$. We consider how changes in the sales of different products in response to this price change Δp_H helps us identify the parameters of interest.

The average price sensitivity $\bar{\alpha} = Pr(\theta_i = p)\alpha_p + Pr(\theta_i = g)\alpha_g$, holding the other parameters fixed, is determined by Δs_H. The higher the correlation between own price change and own sales change, the higher the price sensitivity.

The degree of substitutability between molecules ρ is pinned down by the degree to

the price change Δp_H results in substitution away from the outside option. If there is no substitution away from the outside option $\Delta s_0 = 0$, then $\rho = 1$. As $\Delta s_0 = 0$ increases, ρ approaches 0.

Finally, the heterogeneity in price sensitivity across consumers $\alpha_p - \alpha_g$ depends on the heterogeneity in the diversion ratios of M and L. If $|\alpha_p - \alpha_g| = 0$, then $\Delta s_M = \Delta s_L$. Holding $\bar{\alpha}$ fixed, a large $|\alpha_p - \alpha_g|$ would imply that $\Delta s_M > \Delta s_L$ and the difference between $\Delta s_M - \Delta s_L$ determines $|\alpha_p - \alpha_g|$.

F.4 Physician Preferences and Choice Frictions

We estimate physician perceptions δ^{phy} and preferences $\{\alpha^{\text{phy}}, \rho^{\text{phy}}\}$ by maximizing the likelihood of three choices: baseline choices, choices with a random price change, and second choice. As before, we estimate these parameters disease by disease.

Let $Y_{ijt} = 1$ if physician i chooses product j for choice instance $t \in \{1, 2, 3\}$ and $Y_{ijt} = 0$, otherwise. Recall that the choice probability under our model is:

$$\sigma_{ij}(p_{it}, J) = \frac{\exp(\frac{\delta_j - \alpha_i p_{ijt})}{1-\rho})}{\left(V_{m(j)}\right)^{\rho} \left(\sum_{m'} V_{m'}\right)^{1-\rho}}$$

where $V_m = \sum_{k:m(k)=m} \exp(\frac{\delta_k - \alpha_i p_{ikt}}{1-\rho})$ and $\alpha_i = \alpha / y_i$, where y_i denotes income. The aggregate choice probability is $\sigma_{jt} = \int \sigma_{ijt}\, dF(\alpha_i)$.

The prices are assumed to be the same for all physicians for the first choice $p_{ijt=1} = p_{jt=1} \forall i$ and are measured from AIOCD data. In the second choice instance, the price randomly changes as:

$$p_{ijt=2} = \begin{cases} p_{ijt=1} & \text{if } Y_{ijt=1} = 0 \\ (1 + x_i/100) \times p_{ijt=1} & \text{if } Y_{ijt=1} = 1 \end{cases}$$

where x_i is drawn uniformly at random from $\{5, 10, 15, 20, 25, 40, 50, 75\}$.

In the third choice instance, the price is

$$p_{ijt=3} = \begin{cases} p_{ijt=1} & \text{if } Y_{ijt=1} = 0 \\ \infty & \text{if } Y_{ijt=1} = 1 \end{cases}$$

Note that a price of ∞ is equivalent to assuming that the product is not longer available in the market.

We assume that logit shocks are fixed between the baseline choice and the experimental choices (de Palma and Kilani, 2011). The log-likelihood of the choice sequence is

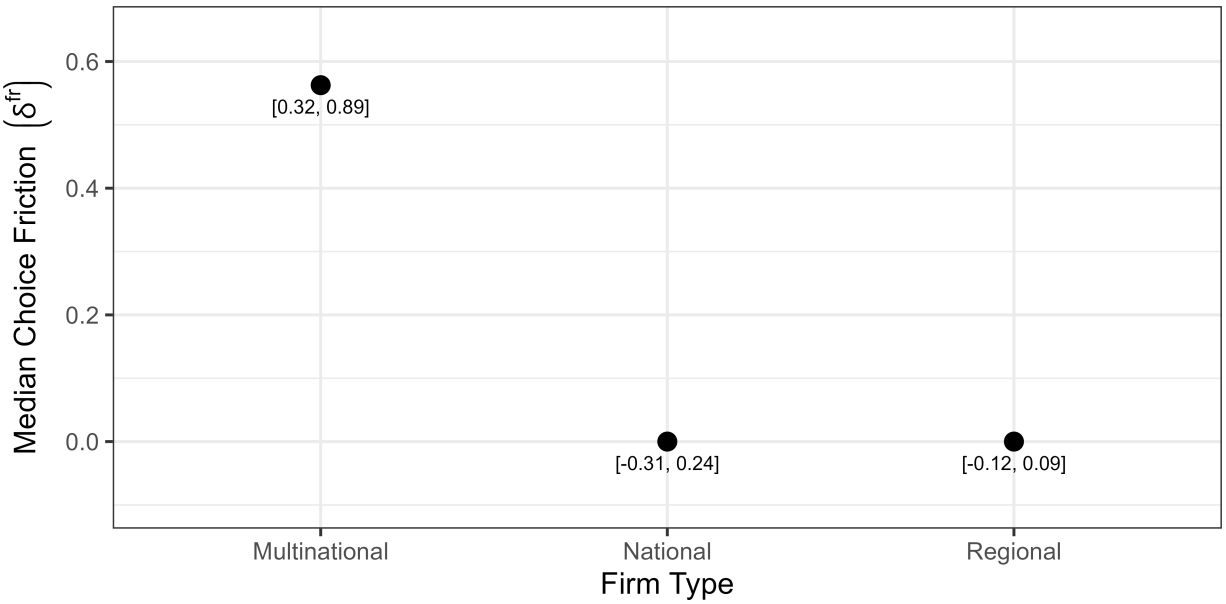
$$
\begin{aligned}
LL(\delta, \alpha, \rho) = \sum_i \sum_j \sum_{j'} & \underbrace{1\{j = j'\} Y_{ijt=1} Y_{ijt=2} \log(\sigma_{ij}(p_{it=2}, J))}_{\text{choose } j \text{ before and after price change}} \\
& + \underbrace{1\{j \neq j'\} Y_{ijt=1} Y_{ij't=2} \log\left(\left[\sigma_{ij}(p_{it=1}, J) - \sigma_{ij}(p_{it=2}, J)\right] \sigma_{ij'}(p_{it=1}, J \setminus j) \right)}_{\text{Switch from } j \to j' \text{ after price change}} \\
& + \underbrace{1\{j \neq j'\} Y_{ijt=1} Y_{ij't=3} \log\left[\sigma_{ij}(p_{it=1}, J)\, \sigma_{ij'}(p_{it=1}, J \setminus j) \right]}_{j \text{ is first choice, } j' \text{ is second choice}}.
\end{aligned}
$$

Our estimator maximizes the above-defined likelihood. Standard errors are then using the Fisher information matrix, as is standard in Maximum Likelihood Estimation.

Isolating Brand Choice Frictions Recall, our goal is to estimate choice frictions about different brands of the same molecule. To isolate the variation between brands of the same molecule, we measure the average product quality of a molecule $\delta_{ms} = \frac{1}{|j:m(j)=m|} \sum_{j:m(j)=m} \delta_{js}$ and differentiate it from the product perceptions $\delta_{j|ms} = \delta_{js} - \delta_{m(j)s}$. We do so separately for patients and physicians. Our measure of choice frictions is difference in the within-molecule perceptions:

$$\delta_j^{\text{fr}} = \delta_{j|ms}^{\text{phy}} - \delta_{j|ms}.$$

Figure F4: Choice Frictions and Firm Type



Notes: The figure presents the relationship between firm type on the $x-$axis and choice frictions (δ^{fr}) on the $y-$axis. Each point represents the media choice frictions with inter-quartile ranges annotated in parenthesis.

Table F4: Brands with the most and least negative choice frictions

Firm	Firm Type	Choice Frictions
Most negative choice frictions		
JENBURKT PHARMACEUTICALS LTD	Regional	-0.58
MANKIND PHARMACEUTICALS LTD.	National	-0.36
AJANTA PHARMA LTD	National	-0.27
MEDLEY PHARMACEUTICALS	National	-0.19
BLUE CROSS LABORATORIES LTD	National	-0.18
Most positive choice frictions		
RANBAXY LABORATORIES LTD	National	0.21
CADILA PHARMACEUTICALS LTD	National	0.21
PFIZER LTD	Multinational	0.23
ASTRAZENECA PHARMA INDIA LTD	Multinational	0.28
SANOFI INDIA LTD.	Multinational	0.70

F.5 Counterfactuals Algorithm

Consider a market with $\mathcal{J} = \bigcup_{f \in F} \mathcal{J}_f$, with consumer perceived quality $\delta_j \, \forall j \in \mathcal{J}$ sold by F firms. A policy implements a price ceiling $\overline{p_j}$ for a subset of products. With abuse of

notation, we write that $\overline{p_j} = \infty$ for a product that is not regulated.

We describe the algorithm that we used to compute counterfactuals. In particular, we describe the algorithm used to compute the supply-side equilibrium under a policy. Recall, our supply side consists of two steps: pricing and exit. We start by discussing the pricing algorithm, given a set of products $J \in P(\mathcal{J})$.

F.5.1 Pricing Equilibrium

We compute the pricing equilibrium using the following iterated best response algorithm.

Algorithm 1 Algorithm to compute equilibrium prices

Initialize $p^0 = p^{\text{equilibrium}}$
While $||p^t - p^{t-1}||^2 \geq 0.0001$
  $p^t = p^{t-1}$
  For $f \in F$
    $p_f^{t+1} = \arg\max_{p_j \forall j \in J_f} \sum_{j \in J_f} (p_j - mc_j)\sigma_j(p_j, p_{-j}^t)$ such that $p^{t+1} < \bar{p}$

Let $\Pi_f(J_f, J_{-f}, \bar{p})$ denote the equilibrium profits for a firm when it produces J_f and other firms produce J_{-f}. Such an equilibriums exits and is unique.

F.5.2 Exit Equilibrium

Next, we estimate the exit equilibrium. Recall that an equilibrium satisfies $J^*(J^*_{-f}) = J^*_f \, \forall f$, where $J^*_f = \arg\max_{J_f \in P(\mathcal{J}_f)} \Pi_f(J_f, J_{-f}, \bar{p})$.

A key challenge in computing equilibria is the prohibitively large outcome space, which contains $2^{|\mathcal{J}|}$ possible configurations. We take three steps to reduce the space of possible outcomes.

First, we observe that firms will always supply unregulated products. Intuitively, since these products are not subject to price ceilings, firms can charge infinite prices in the second period and achieve the same profits as they would by exiting. Thus, supplying regulated products weakly increases profits. This simplification is only valid under the assumption that fixed costs are amortized. We define $\mathcal{J}_f^{\text{reg}} = \{j \in \mathcal{J}_f : j \text{ is regulated}\}$ and $\mathcal{J}_f^{\text{unreg}} = \mathcal{J}_f \setminus \mathcal{J}_f^{\text{reg}}$.

Second, firms will not supply products whose marginal costs exceed the price ceiling, as doing so would result in negative profits. We refer to such products as *always exiters*, defined as $\mathcal{J}^{\text{always}} = \{j : mc_j < \overline{p_j}\}$.

Third, we identify *never exiters* among the regulated products by examining a maximal exit scenario. For each regulated product j, we estimate its equilibrium price $p_j^{\max}$ when all other regulated products exit. Under the standard assumption that prices are strategic complements, if $p_j^{\max}$ is below the price ceiling, the ceiling would never bind for this product

in all exit scenarios.[2] Such products would always be offered. We define the set of *never exiters* as $\mathcal{J}^{\text{never}} = \{j : j \in \mathcal{J}^{\text{reg}} \text{ and } p_j^{\max} < \overline{p_j}\}$.

Consequently, the set of products for which exit decisions must be considered is $\mathcal{J}_f^{\text{amb}} = \mathcal{J}_f^{\text{reg}} \setminus \mathcal{J}_f^{\text{never}} \setminus \mathcal{J}_f^{\text{always}}$, comprising only regulated products that are neither always nor never exiters. This significantly reduces the dimension of the outcome space we need to consider in estimating exit equilibria.

We estimate the exit equilibrium with the following algorithm.

Algorithm 2 Algorithm to compute exit

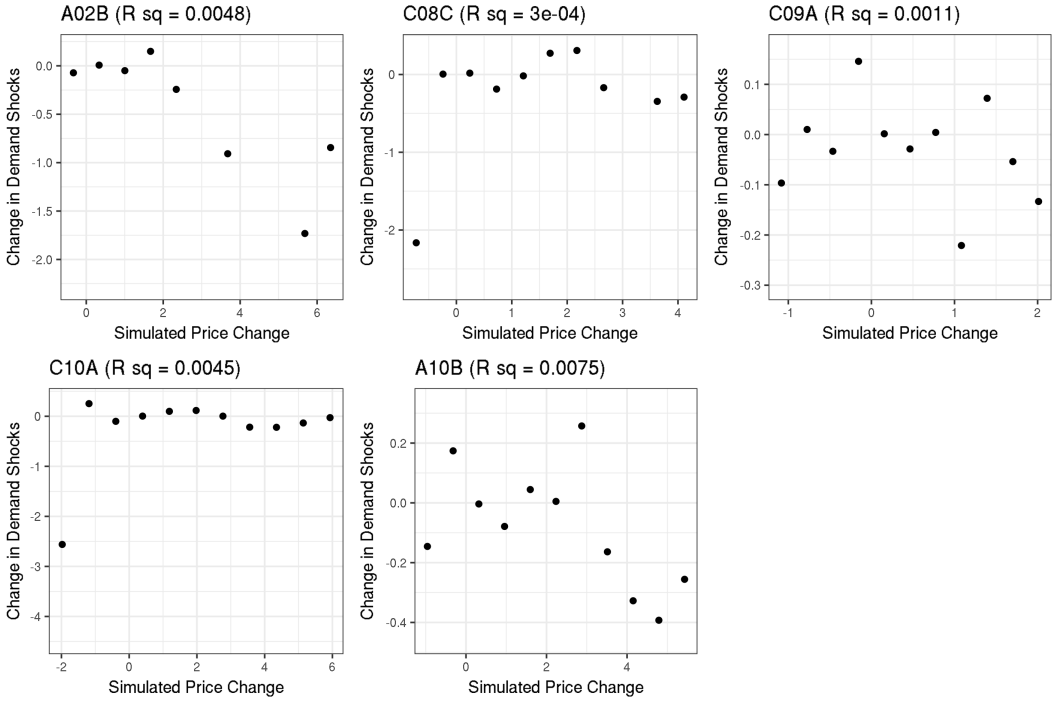
Initialize $J^0 = \mathcal{J}$
While $J^t \neq J^{t-1}$
  $J^t = J^{t-1}$
  For $f \in F$
    $J_f^* = \arg\max_{J_f \in P\left(\mathcal{J}_f^{\text{amb}}\right)} \Pi_f(J_f, J_{-f}^t, \bar{p})$
    $J_f^{t+1} = J_f^* \bigcup \mathcal{J}_f \setminus \mathcal{J}_f^{\text{amb}}$

Although this algorithm will converge to an equilibrium, there is no theoretical guarantee that such an equilibrium is unique. To evaluate the scope of multiple equilibria, we experiment with different initial conditions J^0 and the order of firms in the best response iteration. We find that all of our computations converge to an unique equilibrium, suggesting that multiple equilibria is not a major issue in our analysis.

[2] When prices are strategic complements, the price of product j would be below $p_j^{\max}$, and hence below the price ceiling, when fewer products exit

F.6 Validation, Robustness, and Supplementary Results

Figure F5: Correlation Between Unobserved Demand Shocks and Simulated Price Changes



Notes: The figure presents the correlation between the change in unobserved shock $\Delta\xi_{jst=2016}$ between 2013 and 2016 and the simulated reduction in prices E_{js} for different diseases.

Table F5: Accuracy of Model Exit Predictions for the Indian Policy

Stat.	ACE	Antacids	Calcium Channel	Diabetes	Statins
Accuracy (All)	0.91	0.87	0.96	0.93	0.92
Accuracy (Share > 5%)	0.98	0.98	0.99	0.93	0.97

Notes: The table presents the accuracy of the model exit prediction $\frac{1}{|J|}\sum_j 1\{\text{Exit in Data } = \text{Exit Model}\}$. The top row includes all products while the bottom restricts the sample to products with at least 5% market share.

Table F6: Sensitivity of Parameters to Moments

Antacids

	Own	Other Mol.	Other Brands - High	Other Brands - Med	Other Brands - Low
α_g	0.09	-0.52	-0.38	0.01	-0.12
α_p	-0.05	-0.48	0.52	0.28	0.13
ρ	-0.02	0.60	0.28	-0.80	0.41

ACE Inhibitors

	Own	Other Mol.	Other Brands - High	Other Brands - Med	Other Brands - Low
α_g	-2.18	1.13	-1.35	-1.26	-0.22
α_p	2.76	-1.18	1.07	1.29	0.10
ρ	-0.72	0.18	-0.13	-0.36	0.30

Calcium Channel Blockers

	Own	Other Mol.	Other Brands - High	Other Brands - Med	Other Brands - Low
α_g	1.11	-0.42	-0.51	-1.40	0.03
α_p	-0.40	0.28	0.25	0.00	0.04
ρ	-1.28	0.48	1.47	0.78	0.51

Diabetes

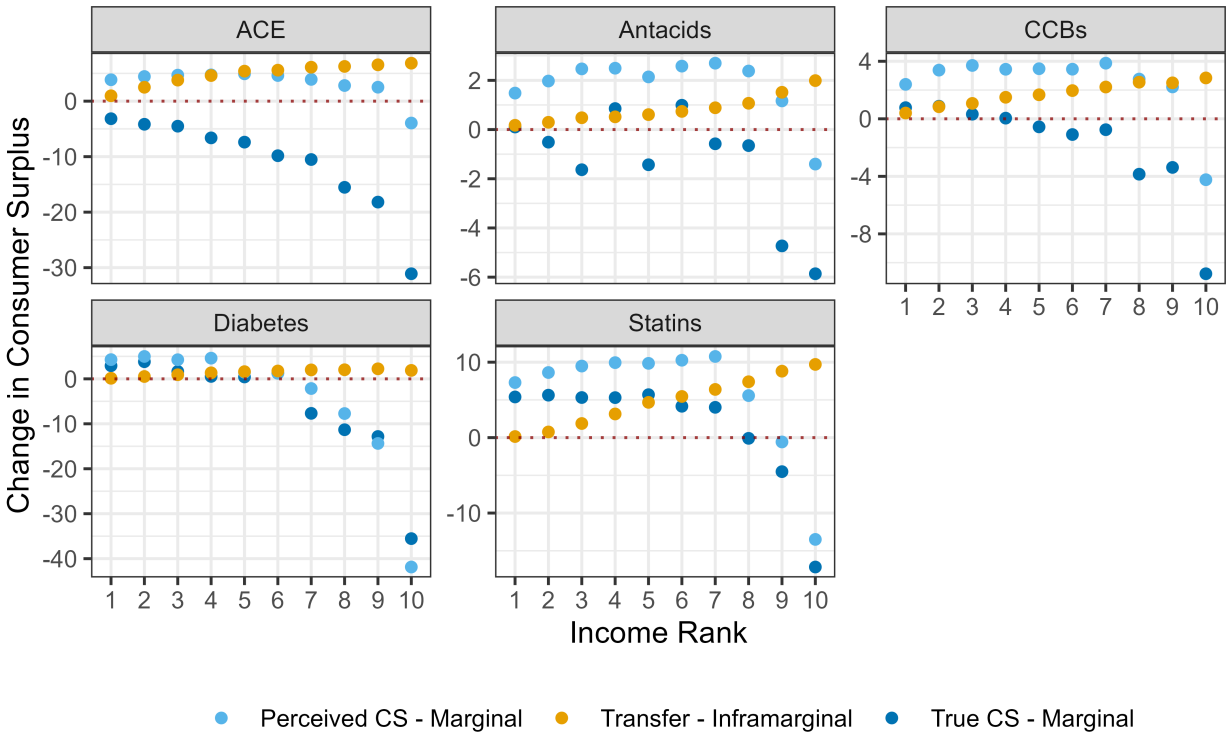
	Own	Other Mol.	Other Brands - High	Other Brands - Med	Other Brands - Low
α_g	0.06	-0.22	0.47	-0.12	-1.05
α_p	-0.10	-0.06	0.05	0.21	0.40
ρ	0.50	0.79	-0.14	0.07	0.96

Statins

	Own	Other Mol.	Other Brands - High	Other Brands - Med	Other Brands - Low
α_g	-0.65	0.22	0.20	0.48	0.32
α_p	0.37	-0.20	-0.13	0.00	-0.32
ρ	0.16	-0.07	0.02	-0.14	0.14

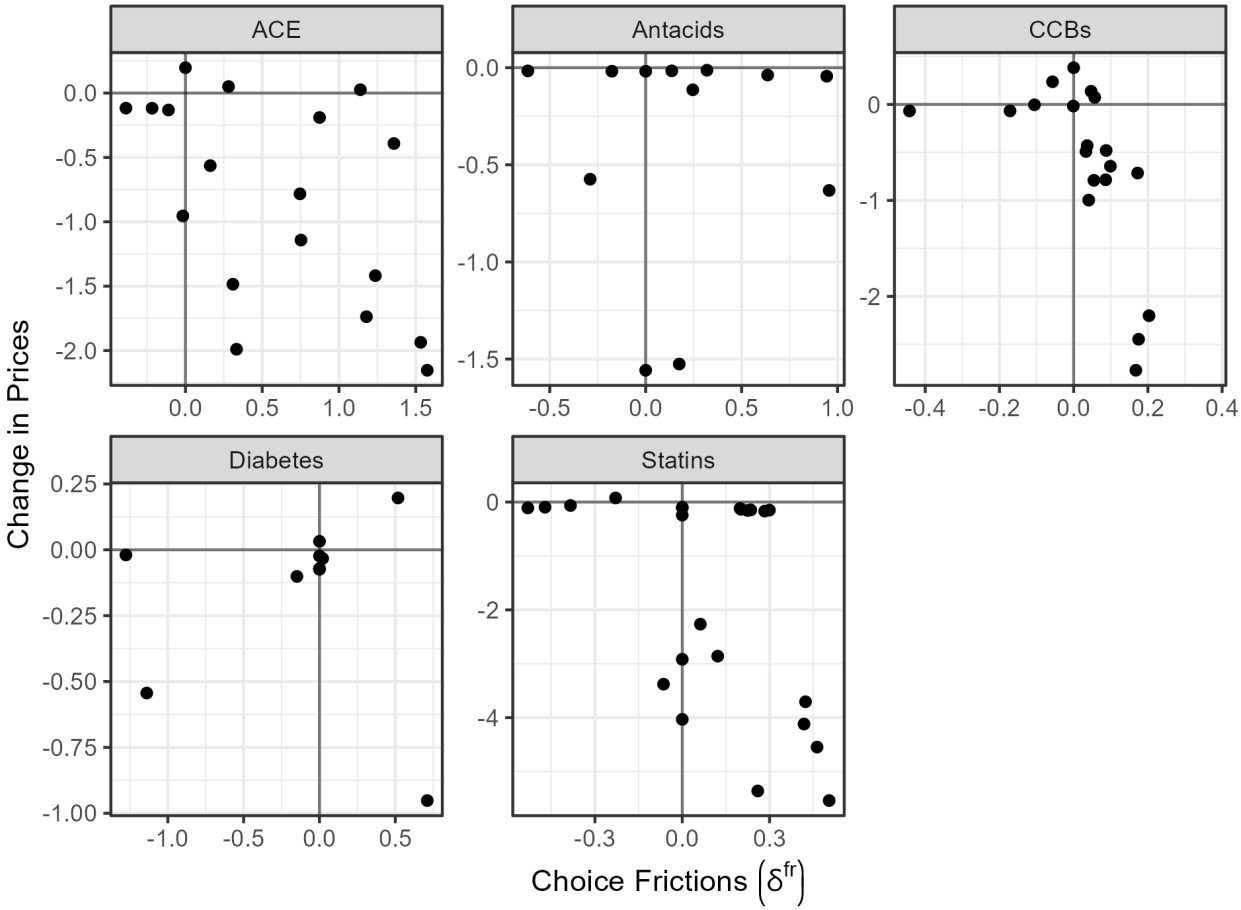
Notes: The table presents the sensitivity of the demand parameters to the estimation moments, as described in Andrews et al. (2017). The rows capture the different parameters and the columns corresponds to the different moments, denoted based on the instrument. "Own" denotes the own-price change instrument Z_{1jst}, "Other Mol." denotes the instruments that captures the price change of other molecules Z_{3jst}, and "Other Brands" is the instrument that captures the price change of other brands Z_{2jst} interacted with pre-policy price level bins G_{js}.

Figure F6: Decomposition of consumer surplus by income



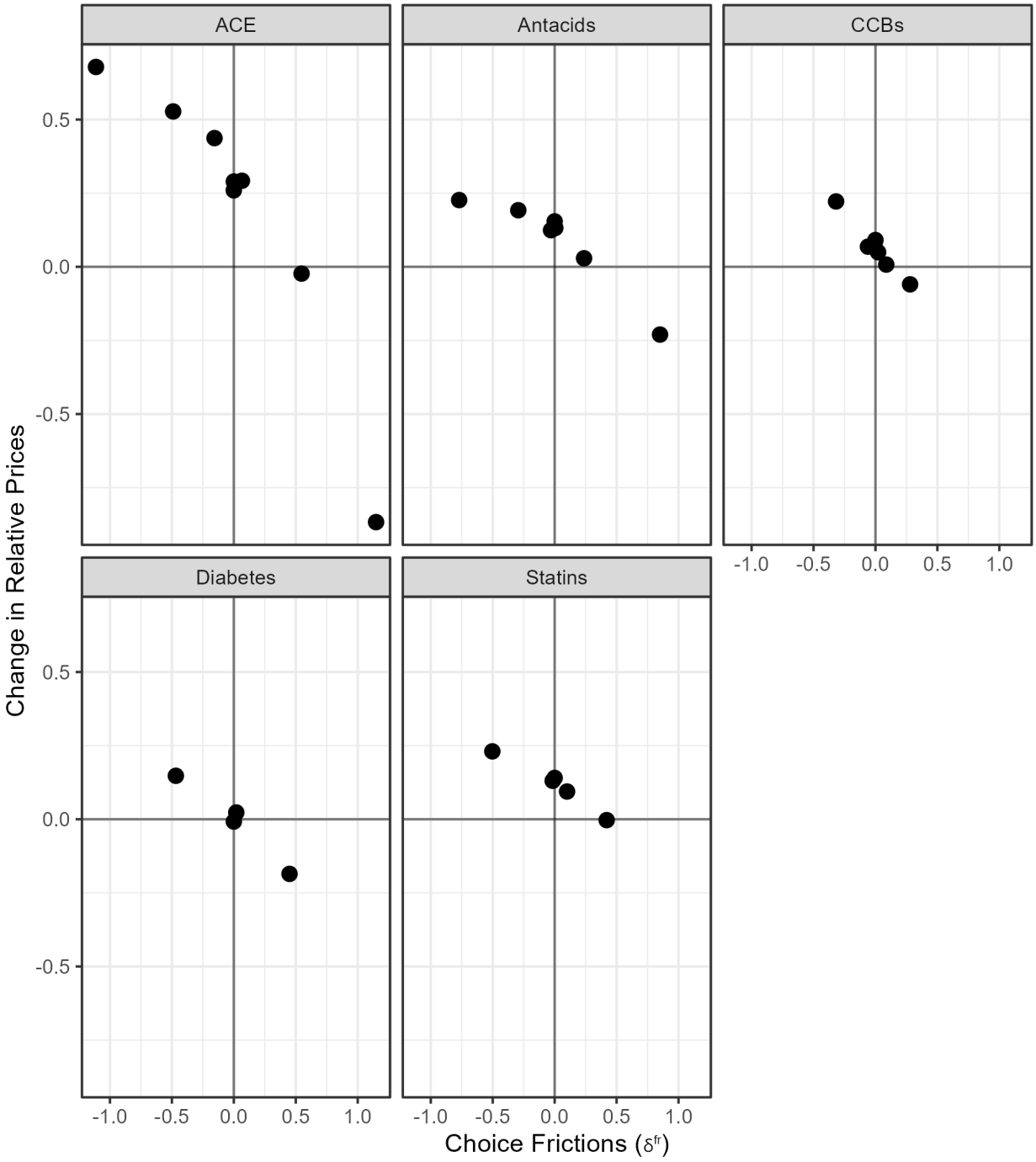
Notes: The figure presents the mean change in consumer surplus on the y-axis by income decile of consumers on the $x-$axis. The change is split into those accruing to marginal and infra-marginal consumers. The gain to marginal consumers are further divided into those with and without adjusting for choice frictions. The outcomes measure the change relative to the no-policy equilibrium in $ per capita per year.

Figure F7: Relationship between policy-induced price change and choice frictions



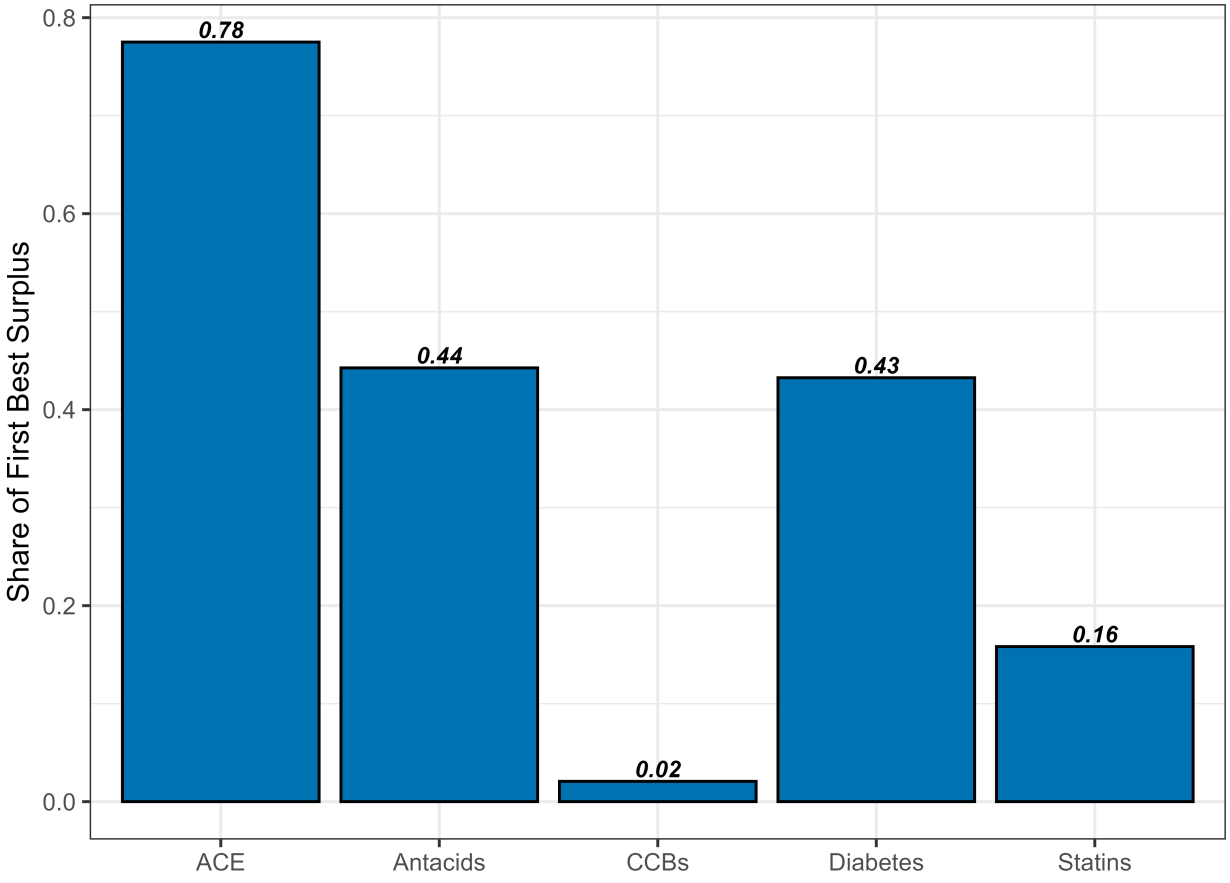
Notes: The Figure presents the estimated choice frictions δ^{fr} on the $x-$axis and the model-implied price changes due to the the Indian Policy on the $y-axis$. Each observation is a product. We only include products with a market share greater than 1%.

Figure F8: Price Changes After Eliminating Choice Frictions



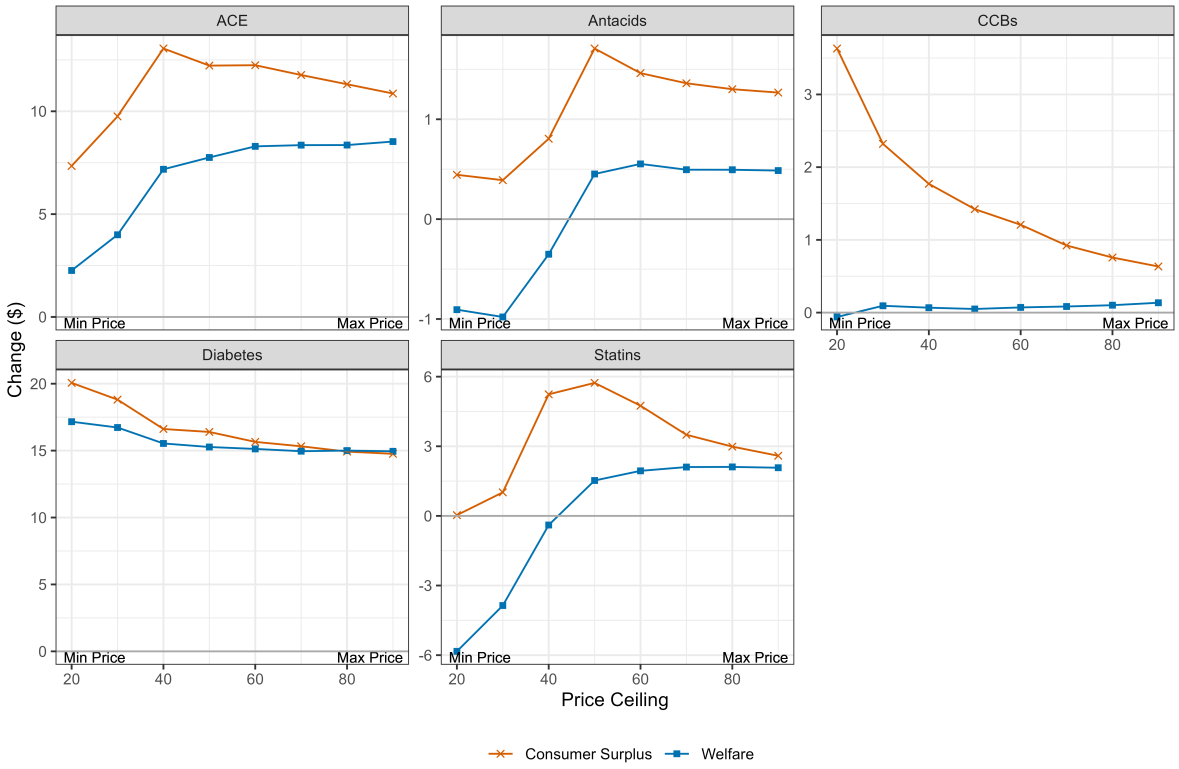
Notes: The Figure presents the estimated consumer choice frictions on the $x-$axis and the model-implied price changes after the informational intervention on the $y-axis$. Each observation is a product.

Figure F9: Share of total surplus obtained by eliminating choice frictions



Notes: The Figure presents the therapeutic market on the $x-$axis and the share of total surplus obtained by different policies on the $y-$axis.

Figure F10: Welfare Effects for Different Price Ceilings After Removing Choice Frictions



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, after removing choice frictions. 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 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.

Table F7: The Effect of Removing Choice Frictions with Fixed Prices on Positive and Normative Outcomes

Outcome	ACE	Antacids	CCBs	Diabetes	Statins
Prices (%)	0.00	0.00	0.00	0.00	0.00
Share Regulated (p.p)	-0.01	-0.04	0.01	0.10	0.02
Share Inside (p.p)	-0.02	-0.03	0.01	0.05	0.02
Share Exit (%)	0.00	0.00	0.00	0.00	0.00
Profit ($)	-3.46	-0.97	-0.46	0.81	-0.51
Revealed C.S. ($)	-8.24	-2.70	-0.41	7.19	-0.29
True C.S. ($)	11.01	2.31	0.59	5.10	1.59
Revealed Welfare ($)	-11.71	-3.66	-0.88	8.00	-0.80
True Welfare ($)	7.55	1.35	0.13	5.91	1.08

Notes: The table presents the change in key positive and normative outcomes after the elimination choice frictions while holding prices fixed, relative to the no-policy equilibrium. Each denotes a therapeutic market and each row is an outcome. We present the median change in outcomes across all states in 2013.

Table F8: The Effect of Removing Choice Frictions with Endogenous Prices on Positive and Normative Outcomes

Outcome	ACE	Antacids	CCBs	Diabetes	Statins
Prices (%)	0.05	0.03	0.03	-0.01	0.02
Share Regulated (p.p)	-0.02	-0.03	0.00	0.08	0.01
Share Inside (p.p)	-0.03	-0.03	0.00	0.04	0.01
Share Exit (%)	0.00	0.00	0.00	0.00	0.00
Profit ($)	-2.27	-0.69	-0.24	1.52	-0.15
Revealed C.S. ($)	-9.35	-2.82	-0.66	5.95	-0.83
True C.S. ($)	9.91	2.19	0.35	3.86	1.05
Revealed Welfare ($)	-11.61	-3.51	-0.89	7.47	-0.98
True Welfare ($)	7.64	1.50	0.11	5.38	0.90

Notes: The table presents the change in key positive and normative outcomes after the elimination choice frictions allowing firms to choose prices, relative to the no-policy equilibrium. Each denotes a therapeutic market and each row is an outcome. We present the median change in outcomes across all states in 2013.

Table F9: Share of First-Best Surplus Achieved by Different Policies

Policy	ACE	Antacids	CCBs	Diabetes	Statins
Indian Price Controls	-0.27	-0.04	-0.00	-0.12	-0.23
Government Entry	0.18	0.46	0.55	0.55	0.41
Generic Substitution	-1.62	-1.91	-2.57	-0.83	-4.78
No Frictions	0.78	0.44	0.02	0.43	0.16
No Frictions (Fixed Prices)	0.77	0.39	0.02	0.47	0.19
Qual. Reg	-0.18	-0.31	-0.30	-0.09	-0.55
Qual. Reg w/ Updating	0.43	0.35	0.41	0.56	0.97

Notes: The table presents the share of total surplus obtained by different policies across therapeutic markets.

F.7 Sensitivity to Correlation Between Price Sensitivity and Choice Frictions

In our baseline model, we assume that choice frictions δ_j^{fr} are identical between consumers i. In this section, we show how the welfare effects of the DPCO vary as we relax this assumption.

If choice frictions are heterogeneous between consumers, but are not systematically correlated with price sensitivity, then the sign of our results is unaffected, and the magnitude of results shifts by a fixed level. Let $\delta_{ij}^{\text{fr}} = \delta_j^{\text{fr}} + W_{ij}$, where W_{ij} is a random variable with mean 0 and $W_{ij} \perp \alpha_i$. Under this slightly alternative set up, the utility function is

$$\begin{aligned} U_{ijst} &= \delta_{js}^{\text{true}} + \delta_{js}^{\text{fr}} + W_{ijst} - \alpha_i p_{jst} + \epsilon_{ijst} \\ &= \delta_{js}^{\text{true}} + \delta_{js}^{\text{fr}} - \alpha_i p_{jst} + \underbrace{\epsilon_{ij} + W_{ijst}}_{\tilde{\epsilon_{ijst}}} . \end{aligned}$$

Therefore, this alternate assumption is equivalent to assuming an alternative distribution of the idiosyncratic errors ϵ_{ijst}. Importantly, the variance of the idiosyncratic shocks increases. As is standard in logit models, we normalize the variance of these shocks and measure the other parameters relative to normalization. Increasing the variance of the shocks implies that the deterministic parts of the model are uniformly scaled down. Consequently, any changes in the deterministic parts of the model, such as price changes due to the DPCO, have a smaller effect on consumer utility, and the welfare effects are smaller in magnitude. The sign of the welfare changes remains unaffected.

However, if choice frictions are correlated with price sensitivity, then both the sign and magnitude of the welfare effects may vary. For example, if price-sensitive consumers suffer

from larger choice friction, then the change in consumer surplus from the DPCO is smaller and may even be negative. To assess the sensitivity of our results, we consider an alternative utility specification:

$$U_{ijst} = \delta_{js}^{\text{true}} + b_i \delta_{js}^{\text{fr}} - \alpha_i p_{jst} + \epsilon_{ijst}\,.$$

In this specification, b_i captures the degree to which choice frictions differ between consumers. In particular, consumers with larger b_i have inflated choice frictions. If $b_i = 0$, consumers are free from choice frictions.

We assume that

$$b_i = 1 + \rho \frac{\alpha_i - \mathbf{E}(\alpha_i)}{sd(\alpha_i)} + \sqrt{1-\rho^2} W_i. \tag{F.1}$$

Under this setup $\mathbf{E}(b_i) = 1$, so the aggregate choice friction remains unchanged. The parameter ρ captures the correlation between choice frictions and price sensitivity. Importantly, given our estimate of price sensitivity $F(\alpha_i)$, we can simulate b_i and examine how the welfare effects of the DPCO vary as a function of ρ.

The results of this simulation are presented in Figure F11. For all disease, except for ACE inhibitors, the change in consumer surplus after DPCO does not vary significantly with ρ. For the ACE inhibitor market, the higher the correlation, the lower the gain in consumer surplus from the DPCO. The difference is negligible for $|\rho| < 0.5$. However, if there is a strong positive (negative) correlation then our baseline estimate overstate (understate) the change in consumer surplus from the DPCO.

F.8 Optimal Price Ceiling

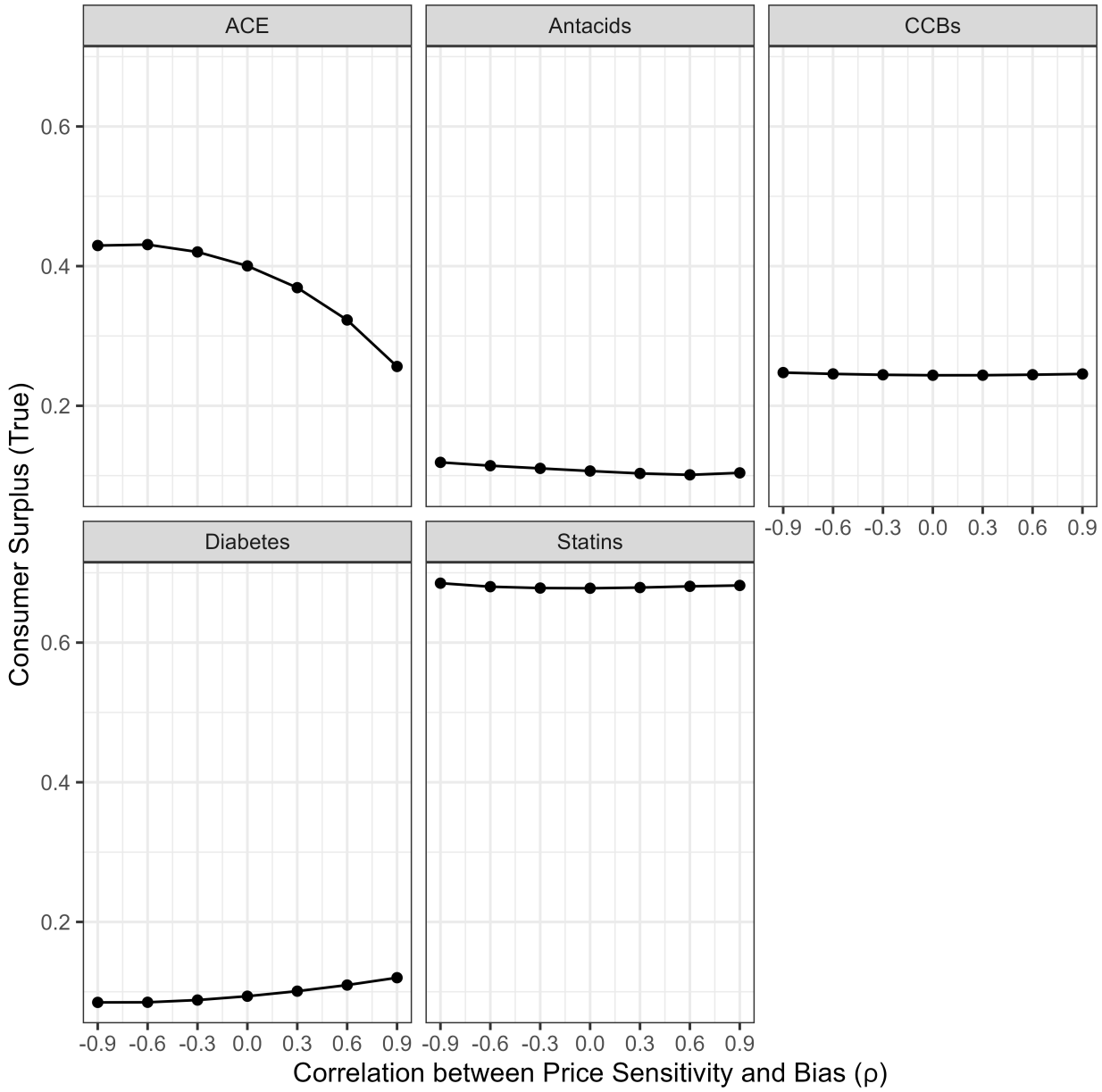
In this section, we formally explore the problem of optimal price ceilings. The regulator chooses set of price ceilings $\bar{p}$ to maximize welfare:

$$\max_{\bar{p}} W = \int CS_i(\bar{p})\, dF(\alpha_i, y_i) + \sum_f \Pi_f\left(\bar{p}\right)$$

Critically, the regulator's choice of price ceiling influences a firm's supply: prices and whether they exit. The set of available products and their prices then determine consumer welfare. In standard cases, the key trade-off from lowering price ceilings is between lower prices and increased exit. In addition, for our analysis, lower prices are not always welfare improving due to choice frictions.

Consider a case where there are no choice frictions. If the regulator observes marginal costs and can set product-specific prices, then the optimal price ceiling is naturally $\bar{p^*} = mc$.

Figure F11: Change in consumer surplus after DPCO and correlation between price sensitivity and choice frictions



Notes: The Figure presents aggregate change in consumer surplus after the DPCO in money-metric units on the $x-$axis. The $y-$axis represents the assumed correlation between price sensitivity α_i and choice friction scaling b_i as defined in Equation F.1. The different panels represent different therapeutic markets (ATC-4 groups).

For a given product, welfare is increasing as the price ceiling is lowered until the price ceiling approaches the marginal cost of the product. Lowering the price ceiling below mc_j decreases welfare due to exit. Therefore, the optimal price ceiling for product j is mc_j. This argument holds irrespective of the price ceilings for other products $\bar{p_{-j}}$. Thus, we can iterate the same argument over all products, resulting in $\bar{p^*} = mc$.

If there are choice frictions, then marginal cost pricing is no longer optimal. Instead, a regulator wants to set prices to correct the "internality" arising from choice frictions. For example, if there is a product j such that $\delta_j^{\text{fr}} > 0$, then regulators want a price ceiling $\bar{p_j^*} > mc_j$ to prevent consumers from overconsuming j. The first-best price is one that achieves the same allocation as when there are no choice frictions and no market power: $\sigma(\delta, p^*) = \sigma(\delta^{\text{true}}, mc)$. As noted in the classic work by Buchanan (1969), the optimal prices would be higher than marginal costs for goods that consumers tend to overvalue. Regulators can set price ceilings $\bar{p^*}(\delta, \delta^{\text{true}}, mc)$ such that equilibrium prices are these optimal prices.

Of course, the key challenge is that regulators only observe prices and are not aware of $\{\delta, \delta^{\text{true}}, mc\}$. Let $F()$ denote the beliefs of the firms about these primitives with support $\Omega \subset \mathbb{R}^2 \times \mathbb{R}^+$. We assume that a regulator has a worse-case loss function:

$$\bar{p^*} = \min_{(\delta, \delta^{\text{true}}, mc) \in \Omega} \max_{\bar{p}} W(\bar{p}).$$

We discuss different assumptions over $F()$ and the resulting optimal policy.

No Information It is easy to verify that if priors are diffuse, then the optimal policy is not to impose price ceilings $\bar{p} \to \infty$. In particular, if there is a non-zero probability that prices equal costs and there are no choice frictions, then there is a non-zero probability that the price ceilings reduce welfare. Under worse-case loss, a lack of information forces a regulator to not impose any restrictions, even if there are large maker failures.

Upper Bound on Costs and Information on Signs of Choice Frictions Next, we assume that regulators know that marginal costs are below a threshold μ_j for all products $F(mc_j \leq \mu_j) = 1$ and know the sign of choice frictions for all products. That is, let $J = J^+ \cup J^-$ be a partition of the product set such that $F(\delta_j^{\text{fr}} > 0) = 1 \, \forall j \in J^+$ and $F(\delta_j^{\text{fr}} \leq 0) = 1 \, \forall j \in J^-$. In addition, assume that $|\frac{\partial p_j}{\partial p_{j'}}| < 1 \, \forall j \neq j'$.

Under these assumptions, the optimal price ceiling is $\bar{p_j^*} = \mu_j \, \forall j \in J^-$ and $\bar{p_j^*} \to \infty \, \forall j \in J^+$. For $j \in J^-$ any price ceiling below the upper bound of costs would result in exit and reduces welfare with positive probability. Imposing a price ceiling above the upper bound allows for distortionary mark-ups. Thus, the optimal price ceiling is set at the upper bound.

For $j \in J^-$ any binding price ceiling exacerbates choice frictions and reduces welfare with positive probability. Therefore, under a worse-case loss function, it is optimal to not have any price ceiling for these products. The impacts of such a price ceiling are presented in Table F10.

Table F10: The Effect of Cost-Based Caps for Weakly Undervalued Products on Positive and Normative Outcomes

Outcome	ACE	Antacids	CCBs	Diabetes	Statins
Prices (%)	-0.08	-0.08	-0.52	-0.37	-0.29
Share Regulated (p.p)	0.69	0.71	0.78	0.64	0.60
Share Inside (p.p)	0.80	0.82	0.80	0.84	0.74
Share Exit (%)	0.00	0.00	0.00	0.00	0.00
Profit ($)	8.69	2.40	-2.54	5.86	5.91
Revealed C.S. ($)	0.28	1.58	6.27	6.05	6.26
True C.S. ($)	1.32	1.70	5.67	7.89	6.55
Revealed Welfare ($)	8.97	3.99	3.74	11.90	12.17
True Welfare ($)	10.01	4.11	3.13	13.75	12.46

Notes: The table presents the change in key positive and normative outcomes after a cost-based cap on weakly undervalued products, relative to the no-policy equilibrium. Each denotes a therapeutic market and each row is an outcome. We present the median change in outcomes across all states in 2013.

F.9 Government Entry

A regulator can reduce market power by competing with private firms with a public option. Such policies have been gaining traction in many countries. For example, California announced plans to supply its own generic insulin to compete with private manufacturers. We evaluate the impact of such a public option in India.

Given that the Indian government has not supplied pharmaceuticals in the past, we must make assumptions about various characteristics of this public option. We assume that the public brand has the same true utility and marginal costs as the highest-utility private brand on the market, while consumers will underestimate its utility due to lack of trust in the government. For a given drug, we assume that the misperception of the public option is equal to the average misperception among all Indian brands. The Government commits to selling at marginal cost.

The effects of offering such a public option are reported in Supplementary Table F11. We find that 12% to 46% of consumers switch from private brands to the government option. Moreover, there is a substantial market expansion, especially in the Diabetes and Calcium

markets where private markups are the highest. Besides offering a cheaper option, government entry also impacts private prices through competition. The equilibrium price responses are varied across therapeutic markets: private brands reduce their prices in the ACE market by 5% in light of the additional competition but raise prices elsewhere to target the price-insensitive consumers. Compared to other policies, the equilibrium price effects are quite small.

The perceived consumer surplus increases by between $2.11 and $11.84. Since consumers tend to undervalue the government option, the benefit in true consumer surplus is usually even larger. After accounting for the profit loss by private firms, the per-capita welfare gain ranges from $1.05 in the ACE market to $5.47 in the Diabetes market. The increase in welfare is close to that under marginal-cost pricing, achieving approximately 75% of the maximum possible surplus.

Our analysis does not account for the costs of setting up manufacturing and distribution of the government brand. Unfortunately, we do not have reliable estimates of these fixed costs or the marginal cost of public funds in India (Hendren and Sprung-Keyser, 2020). Our results can conservatively be viewed as an upper bound on the welfare benefits of the government option.

Table F11: The Effect of Government Entry on Positive and Normative Outcomes

Outcome	ACE	Antacids	CCBs	Diabetes	Statins
Prices (%)	0.01	0.06	0.17	0.07	0.01
Share Regulated(p.p)	-0.07	-0.14	-0.23	-0.17	-0.06
Share Inside (p.p)	-0.09	-0.19	-0.25	-0.32	-0.09
Share Exit (%)	0.00	0.00	0.00	0.00	0.00
Gov. Share (p.p)	0.11	0.25	0.35	0.44	0.15
Bias	0.44	0.18	0.01	-0.04	0.02
Private Profit ($)	-1.39	-1.40	-2.95	-7.13	-2.86
Revealed C.S. ($)	1.66	1.92	5.13	14.02	5.22
True C.S. ($)	3.10	2.82	5.36	13.38	5.47
Revealed Welfare ($)	0.27	0.52	2.18	6.89	2.36
True Welfare ($)	1.70	1.43	2.41	6.25	2.60

Notes: The table presents the change in key positive and normative outcomes after the Government Entry policy, relative to the no-policy equilibrium. Each denotes a therapeutic market and each row is an outcome. We present the median change in outcomes across all states in 2013.

F.10 Mandatory Generic Substitution

Regulators in many countries implement a "generic substitution" policy to discourage consumers from purchasing expensive brands. Although exact implementation varies, such policies increase the price differences between branded and generic drugs or require consumers to buy the cheapest brand of a drug (Gothe et al., 2015).

In our counterfactual, we assume that consumers must buy the cheapest brand of a drug[3] and observe the brands they are receiving.[4] We consider two versions of this policy. In the first version, all brands, even those with low utility, are allowed to remain on the market ("Generic Substitution"). In the second version, the Government introduces a minimum quality standard, allowing only brands above this quality threshold to supply the market ("Generic Substitution with Qual Control"). We assume that the quality threshold is the average quality of all the brands before the policy.

Results Under a generic substitution policy, firms compete in *undifferentiated* Bertrand instead of differentiated Nash-Bertrand, conditional on meeting any quality requirements. In Figure F12, we present the changes in prices and exit for the highest-selling drugs in each therapeutic market. In equilibrium, only the brands with lowest marginal cost remain in the market and charge prices equal to second-lowest marginal cost. As discussed earlier, there is a positive correlation between costs and quality, implying that high-quality brands are more likely to exit. A quality threshold ensures that at least some high-quality brands remain in the market. Prices drop by more than 80% in all cases (Tables F12 and F13).

In Figure F13, we present the normative implications of these positive changes. We find that a generic substitution policy is beneficial for consumers in Diabetes and Statins, as gains from lower prices dominate loss from exit. However, for markets like CCBs, the policy reduces consumer surplus because there are no high-utility, low-cost options. This exception highlights the risk of generic substitution when there is limited quality control. Case in point, the consumer surplus increases in the CCB market once we implement a quality threshold.

In some markets, the true gains are greater than the perceived gains, as the policy pushes out overvalued brands. Many overvalued brands have higher costs but not higher quality. These costs could reflect, for example, persuasive advertising expenditures. Generic substitution prevents consumers from buying such brands and partly corrects the distortion due to choice frictions.

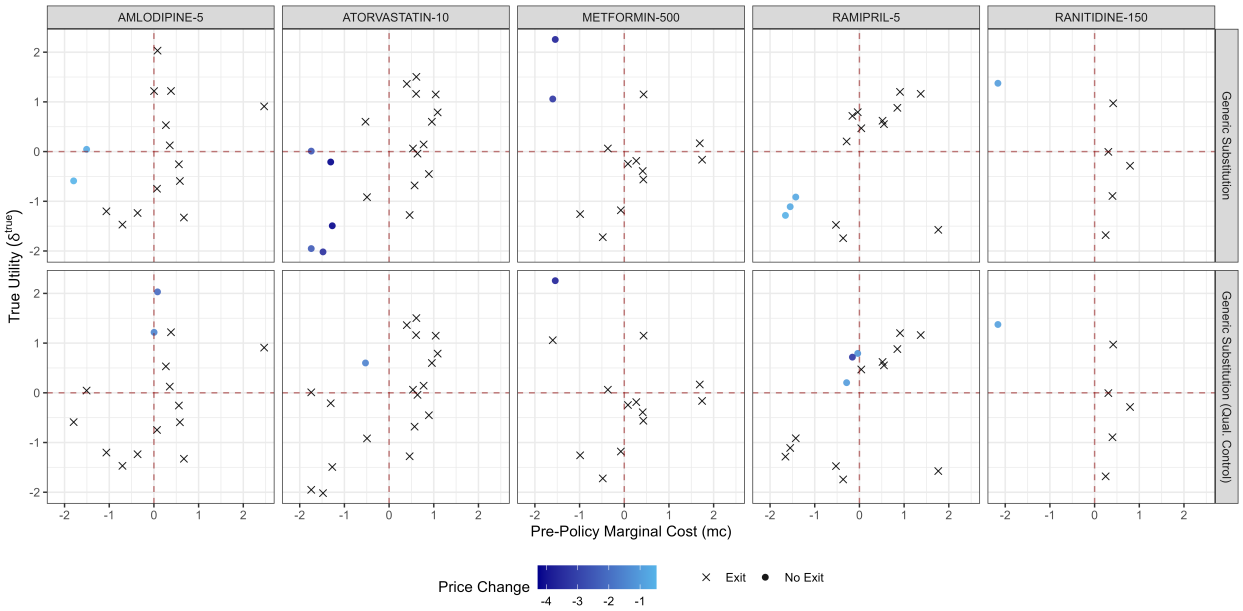
Thus, generic substitution is beneficial for consumers, especially when the regulator can

[3] In the absence of public insurance, there are limited avenues by which a regulation can increase the price difference.

[4] Note that this is contrast to a ban on branding where consumers do not observe the specific manufacturer.

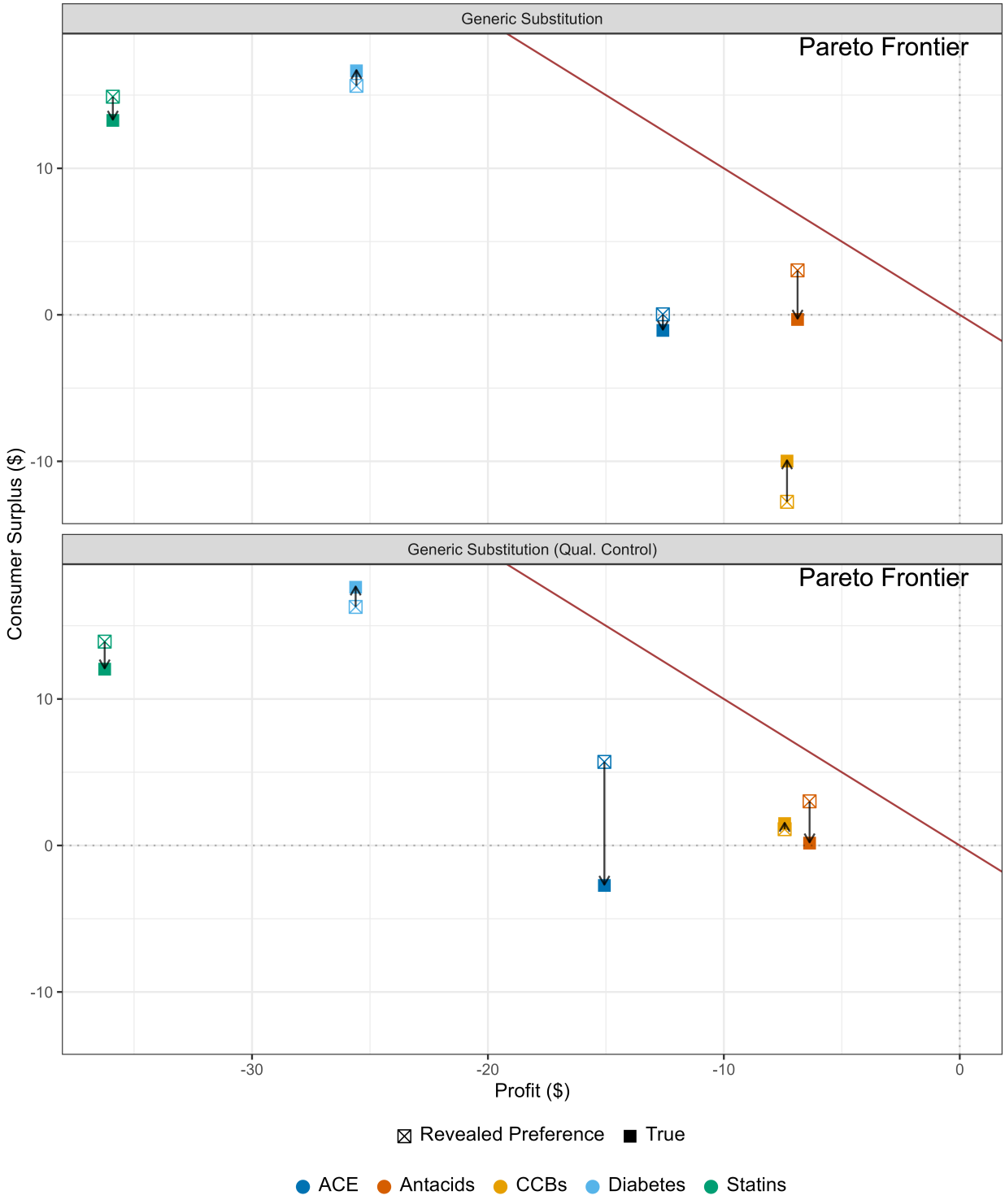
implement a quality threshold. These benefits to consumers come at the expense of firms. Profits decline as firms can no longer charge markups and because many firms have to exit. On net, total welfare declines.

Figure F12: Effect of Generic Substitution of Exit and Prices



Notes: The Figure presents the marginal cost mc and true product utility δ^{true} for different brands of different drugs. Both cost and utility have been standardized to have mean 0 and variance 1. The shape denotes whether a product exits the market or not. The color denotes the magnitude of price change.

Figure F13: Welfare Impacts of Generic Substitution



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 policy-therapeutic market pair, with markets differentiated by color and policies differentiated by shape of the point. 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 measure the magnitude of the change. The outcomes measure the change relative to the no-policy equilibrium in $ per capita per year.

Table F12: The Effect of Generic Substitution on Positive and Normative Outcomes

Outcome	ACE	Antacids	CCBs	Diabetes	Statins
Prices (%)	-0.89	-0.84	-0.94	-0.99	-0.99
Share Regulated (p.p)	-0.40	-0.10	-0.09	-0.17	-0.25
Share Inside (p.p)	0.06	0.12	0.04	0.17	0.22
Share Exit (%)	0.82	0.69	0.82	0.82	0.84
Profit ($)	-11.56	-7.37	-7.31	-26.31	-31.74
Revealed C.S. ($)	-2.57	2.26	-6.64	16.81	9.60
True C.S. ($)	-4.70	1.60	-4.24	16.87	8.39
Revealed Welfare ($)	-14.13	-5.11	-13.94	-9.50	-22.14
True Welfare ($)	-16.26	-5.76	-11.55	-9.44	-23.35

Notes: The table presents the change in key positive and normative outcomes after the Generic Substitution policy, relative to the no-policy equilibrium. Each denotes a therapeutic market and each row is an outcome. We present the median change in outcomes across all states in 2013.

Table F13: The Effect of Generic Substitution with Quality Threshold on Positive and Normative Outcomes

Outcome	ACE	Antacids	CCBs	Diabetes	Statins
Prices (%)	-0.85	-0.85	-0.89	-0.95	-0.95
Share Regulated (p.p)	-0.36	-0.08	-0.06	-0.17	-0.24
Share Exit (%)	0.85	0.83	0.87	0.92	0.93
Share Inside (p.p)	0.07	0.12	0.05	0.17	0.22
Profit ($)	-12.07	-7.35	-6.81	-25.86	-30.91
Revealed C.S. ($)	-1.34	3.41	-3.73	17.24	11.43
True C.S. ($)	-3.31	2.52	-3.11	17.69	9.55
Revealed Welfare ($)	-13.41	-3.94	-10.54	-8.62	-19.48
True Welfare ($)	-15.38	-4.83	-9.92	-8.17	-21.36

Notes: The table presents the change in key positive and normative outcomes after the Generic Substitution policy with a quality threshold, relative to the no-policy equilibrium. Each denotes a therapeutic market and each row is an outcome. We present the median change in outcomes across all states in 2013.

F.11 Quality Standard

Next, we evaluate a policy that introduces quality regulation in the market. Under this policy, brands that are below a quality threshold $\bar{\delta}$ — the average product utility of all brands — are considered substandard.

If a brand is substandard, then the manufacturer of the brand has two choices. First, they can exit the market. Second, they can invest to improve their quality. For a firm, this choice depends on the fixed cost of improving quality and the marginal cost of producing a high-quality product. Unfortunately, we have limited information in our data and research design on these fixed costs. Therefore, we present two extreme cases. In the first, all substandard brands exit, i.e. fixed costs are prohibitively large. In the second case, firms can upgrade their quality without fixed costs.

To measure the increase in marginal costs, we perform a simple linear extrapolation. We estimate the relationship between true utility and costs using a linear regression.[5] We then use the linear model to predict the marginal costs after updating.

Results In Figures F14, we present change in true product quality after the regulation. By construction, the quality of the brands above the quality threshold does not change. The brands below the threshold either exit or update to the quality threshold.

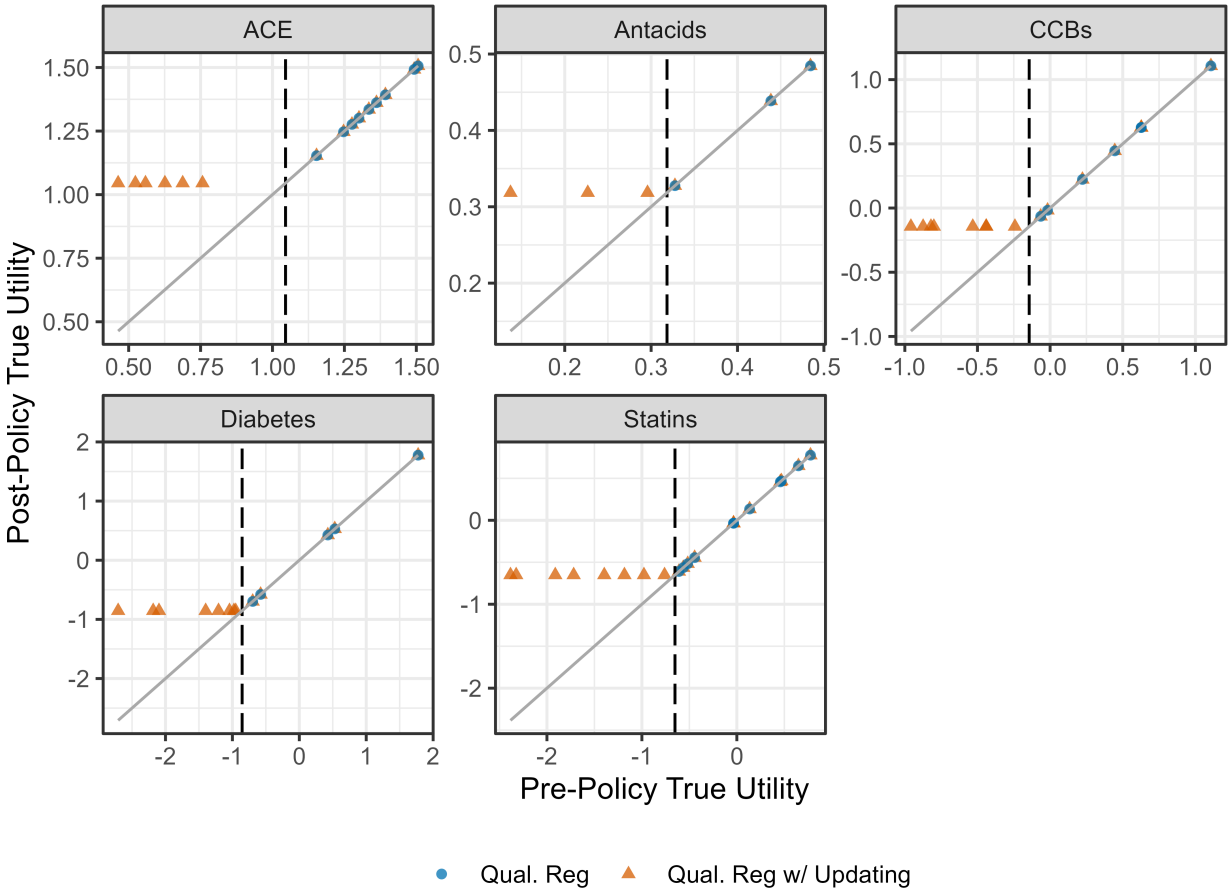
The impact on prices is ambiguous (Figure F15). Consider the case where substandard brands exit. In this case, the policy reduces the number of competitors and reduces product differentiation. The former increases market power, while the latter decreases market power for brands that persist in the market. The changes in prices vary depending on which of these forces dominates. We find that prices decrease as the reduction in product differentiation has a greater impact than exits (Table F14). Note that the decrease in prices is smaller than in most other policies. When substandard brands are updated, prices increase. This increase in prices is partly because substandard brands are now more costly to produce (Table F15).

When substandard products exit, quality regulation reduces consumer surplus and profits (Table F14 and Figure F16). For consumers, the loss from exit dominates the benefits from lower prices. Although the products that exit are low-utility, they offered a cheap option for price sensitive consumers. Their exit thus harms price-sensitive consumers, and although this loss is partially offset by lower prices for high-utility products, the price drop doesn't fully compensate for it. Unsurprisingly, profits and total welfare decrease.

However, when substandard brands update their quality instead of exiting the policy, it is beneficial. Consumers benefit from access to many high-utility products. The benefits for consumers outweigh any decreases in profits, and the policy improves welfare in all therapeutic markets (Table F15 and Figure F16).

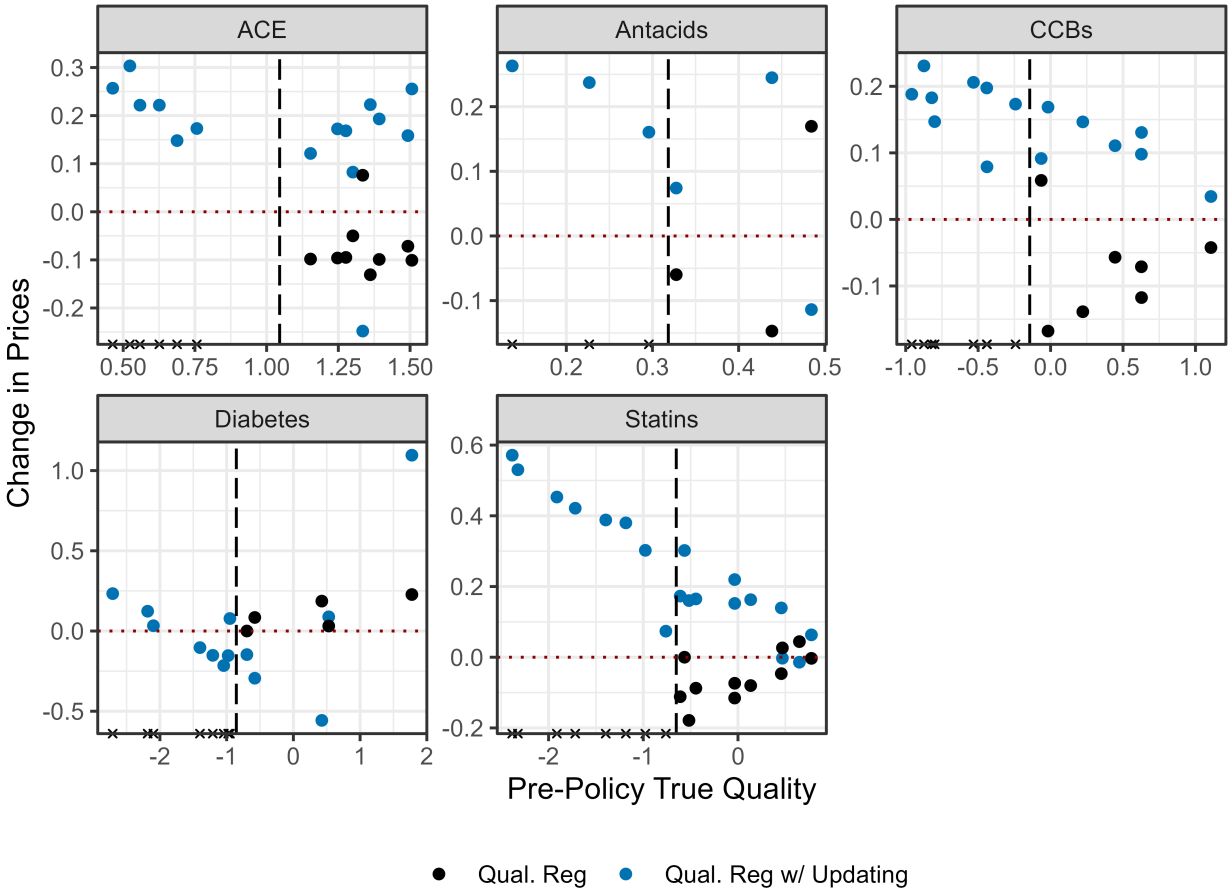
[5] Specifically, we estimate $mc_j = \beta\delta_j^{\text{true}} + \gamma_{m(j)} + \epsilon_j$.

Figure F14: Change in Product Utility after Quality Regulation



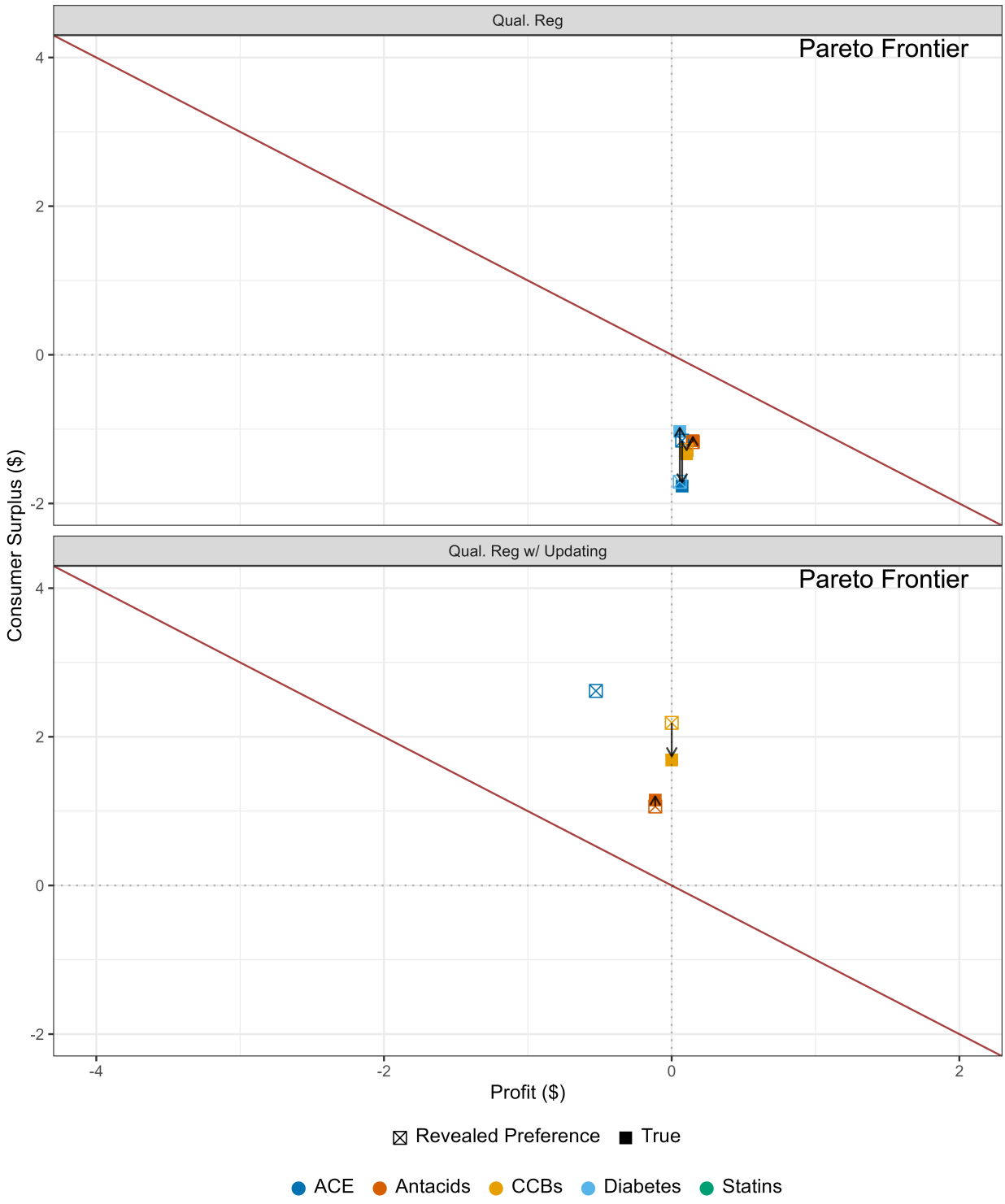
Notes: The Figure presents true product utility before and after the policy. Outcomes are separated by whether substandard drugs exit or update their quality.

Figure F15: Change in Price and Exit after Quality Regulation



Notes: The Figure presents pre-policy true product utility and the change in prices after the policy. Outcomes are separated by whether substandard drugs exit or update their quality.

Figure F16: Welfare Impacts of Quality Regulation



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 policy-therapeutic market pair, with markets differentiated by color and policies differentiated by shape of the point. 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 measure the magnitude of the change. The outcomes measure the change relative to the no-policy equilibrium in $ per capita per year.

Table F14: The Effect of Quality Threshold on Positive and Normative Outcomes: Exit

Outcome	ACE	Antacids	CCBs	Diabetes	Statins
Prices (%)	-0.16	-0.25	-0.09	-0.36	-0.22
Share Essential (p.p)	-0.06	-0.07	-0.03	-0.04	-0.04
Share Exit (%)	0.36	0.47	0.49	0.52	0.45
Profit ($)	-0.04	0.03	0.03	0.01	-0.03
Revealed C.S. ($)	-0.33	-0.18	-0.27	-0.32	-0.38
True C.S. ($)	-0.29	-0.18	-0.29	-0.19	-0.42
Revealed Welfare ($)	-0.36	-0.15	-0.25	-0.31	-0.41
True Welfare ($)	-0.32	-0.15	-0.26	-0.18	-0.44

Notes: The table presents the change in key positive and normative outcomes relative to the no-policy equilibrium. Each denotes a therapeutic market and each row is an outcome. We present the median change in outcomes across all states in 2013.

Table F15: The Effect of Quality Threshold on Positive and Normative Outcomes: Updating

Outcome	ACE	Antacids	CCBs	Diabetes	Statins
Prices (%)	0.03	0.05	0.02	0.01	0.02
Share Essential (p.p)	0.04	0.02	0.03	0.12	0.07
Share Exit (%)	0.00	0.00	0.00	0.00	0.00
Profit ($)	-0.10	-0.02	0.00	0.22	0.10
Revealed C.S. ($)	0.45	0.18	0.36	1.40	0.84
True C.S. ($)	0.79	0.21	0.28	0.87	0.68
Revealed Welfare ($)	0.35	0.16	0.35	1.63	0.94
True Welfare ($)	0.69	0.18	0.28	1.09	0.78

Notes: The table presents the change in key positive and normative outcomes relative to the no-policy equilibrium. Each denotes a therapeutic market and each row is an outcome. We present the median change in outcomes across all states in 2013.

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