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Effects of Pharmaceutical Price Regulation: Evidence from India

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Effects of pharmaceutical price regulation: Evidence from India

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Abstract

We study the effects of pharmaceutical price regulation in India in the context of the Drug Price Control Order 2013 (DPCO), which regulated the prices of essential and life-saving drugs. The objective of regulators was to ensure that these drugs are more affordable; hence the expectation was increased sales volumes for these drugs. We empirically examine the impact of DPCO 2013 on overall sales volumes and also on prescription behavior in rural and disadvantaged areas of the country. Using data on 108 molecules (51 regulated and 57 unregulated) over 62 months (50 months pre-regulation and 12 months post-regulation) and employing a regression discontinuity design (in addition to panel regressions, matching estimators, and forecast models), we find that sales volumes and prescriptions from rural doctors (most without formal medical degrees) decline for regulated drugs while these measures increased for the unregulated ones. We then offer suggestive evidence regarding the mechanism behind our findings. Since prices of regulated drugs declined but those of the unregulated ones did not, we rule out lower prices for the latter as a potential explanation for our findings. Reduced margins of regulated drugs could

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however, have pushed pharmaceutical firms to shift their marketing expenditures to unregulated drugs and may also have lowered retailers' incentives to stock the products. We provide some evidence for a shift in marketing efforts using data on the detailing levels and sales of two brands (one regulated and one unregulated) from a specific firm. We also provide anecdotal evidence about retailers in certain geographic markets understocking regulated drugs, which might have influenced our sales, although not our prescription, outcomes.

Keywords: pharmaceutical price regulation, DPCO, detailing, rural prescriptions, and price regulated molecules.

Effects of pharmaceutical price regulation: Evidence from India

1. Introduction

Price regulation in the pharmaceutical industry can be a double – edged sword. In countries with universal health care systems, governments cover the bills and hence show a tendency to keep a control over the prices through regulatory mechanisms (Green 1998). Extant research on price regulation has focused on developed nations such as the US, where prices are mostly unregulated (Abbott 1995, Abbott and Vernon 2007, Vernon 2005), and Europe (Mrazek 2002, Puig-Junoy 2010) where prices are controlled (a) directly (eg. France and Belgium); (b) through reimbursements (e.g. Germany and Italy); or (c) through profit controls (eg. Spain and United Kingdom). Researchers in economics, marketing and public policy have studied the effects of pharmaceutical price regulation in these regions, and find that regulation may result in a – i) delay of new drug launches (Danzon et al. 2005, Kyle 2007); ii) deterioration in pharmaceutical innovation (Bardey et al. 2010, Vernon 2003); and, iii) decline in research and development investments (Golec et al. 2010, Golec and Vernon 2010).

The effects of such regulation in emerging economies, such as India, remain largely, unexamined. Despite the theoretical attention on price regulation and a number of studies assessing the impact of such regulation on societal welfare in developed nations (eg. Podnar et al. 2007), there is a clear lack of empirical evidence assessing the impact of regulation on the availability, accessibility and sales of prescription drugs in emerging economies. In this paper, we attempt to address this issue by empirically examining the impact of price regulation on sales volumes and prescription behavior and pay special attention to these measures in rural and disadvantaged areas of the country.

Why is it important to assess the sales volume of price-regulated drugs? In an emerging country like India, which is typically characterized by a lack of universal health insurance or health care systems, the typical policy objective of pharmaceutical price regulation is to make the drugs more affordable (and accessible). India is considered a privatized health economy (Duggal 2007), where around 80% of healthcare expenses are borne privately, with a majority being out-of-pocket expenses (Banerji 2013), so the ostensible reason for price regulation is to increase affordability of essential drugs. While this may be the objective of regulation policy, price controls may have adverse effects on the supply-side. With declining margins due to price ceilings, firms may adapt, by shifting their marketing focus to unregulated drugs in the same therapeutic class (Bellur et al. 1985). This in turn, might lead to the unintended consequence of lowering the sales of the price-regulated drugs.

Further, in India, where direct-to-consumer (DTC) advertising for prescription drugs is prohibited, detailing is the main vehicle of marketing to physicians. Physician prescription behaviors have been shown to be sensitive to detailing and marketing activities (eg. Bauer and Wortzel 1966, Gonul et al. 2001, Manchanda and Chintagunta 2004, Narayanan et al. 2004, Venkataraman and Stremersch 2007). Hence redirecting detailing resources to more profitable unregulated drugs may result in lower prescriptions of regulated drugs and eventually to lower sales volumes (in terms of units sold). This is especially true for rural doctors, many of whom lack a formal *allopathic* medical degree but prescribe drugs. They are detailed by firms and depend mainly on detailing for drug information. Further, to optimize resource utilization, firms may deploy their salesforce in a more selective manner, eliminating unproductive territories (Bellur et al. 1985). A territory may be unproductive for two reasons – i) low volume sales (observed in lower tier cities), and ii) difficulty of access (remote rural areas). Hence, the

percentage of sales from lower tier cities and prescriptions by rural doctors may also be adversely affected for the regulated drugs in the presence of price regulations.

Price controls are not the only reason why firms may react by redirecting detailing to other molecules. In developed economies such as the U.S., when a patent expires for a molecule, a number of generics enter the market at significantly lower prices. This shock to the market results in the firm redirecting its detailing efforts to non-bioequivalent drugs (closely related molecules typically prescribed for the same indication) in the same therapeutic class (Caves et al. 1992, Gonzalez et al. 2008). This adversely affects the sales of the brand that owned the patent, but favorably affects the non-bioequivalent drugs. For example, when the drug *Prilosec* (*omeprazole*) went off patent, *AstraZeneca* shifted its focus to *Nexium*, a closely related molecule (*esomeprazole*). Competition exists within a molecule as well as across molecules that treat the same condition, resulting in high cross-price elasticities between therapeutic substitutes (Stern 1996). Another stream of literature focusing on patent expiration provides evidence that a molecule's total utilization (brand and generics) declines after patent expiration (Huckfeldt and Knittel 2012, Huskamp et al. 2008). The effect is attributed to (strategic) reduction of detailing by the brand to eliminate spillover promotion effects and deter entrants (Ellison and Ellison 2011), and on strategic entry and increased marketing of new formulations (Huckfeldt and Knittel 2012). However, recently, Aitken et al. (2013) show an increase in molecule utilization as a brand loses exclusivity (patent expiration), especially for third party payers. However, in India, with no universal insurance, we do not expect to observe this form of response to increased competition from price reduction. Further, our context is one in which the market structure in terms of the number of players is not changing. Hence, in the case of price reductions in the form

of regulation, a more likely response for firms is to redirect their detailing efforts to unregulated molecules with higher profit margins.

In this paper, we address a largely unanswered question in the empirical marketing literature: does price regulation of prescription drugs result in improved consequences in emerging economies - in terms of overall sales volume, sales in lower tier cities and prescriptions by rural doctors? We use the context of the Government of India's (GoI) Drug Price Control Order (henceforth DPCO) in 2013 that brought 348 formulations, deemed essential medicines, under price regulation. Using panel data from IMS Health India database and SMSRC (Strategic Marketing Solutions and Research Centre), we examine the impact of price regulation on 51 regulated and 57 closely related (similar therapeutic class) unregulated oral solid molecules (tablets or pills). We study changes in overall sales volume, sales volume in lower tier cities and prescriptions by rural doctors for the drugs. These outcomes, we believe, are of importance to policy makers and pharmaceutical firms in assessing the impact of the regulation.

A simple description of the outcome measures (please refer to Online Appendix 1) of the 51 molecules subject to regulation reveals that while 36 of them show an improvement in sales (comparing pre-regulation and post-regulation average sales), 15 show a sales decline for an overall average increase in units of 8.8%. Furthermore, looking at the set of 57 closely related molecules not subject to regulation, reveals that those molecules experienced larger sales increases with 55 of them showing an increase and only 2 showing a decrease (overall average increase in units of 34.1%). We then investigate these changes using a panel regression model that controls for various confounding factors via fixed effects and time trends, and find that sales of the regulated molecules decline by 3.7% versus an increase in 5.3% for the unregulated ones. Zooming in on the subset of regulated molecules that we can match (via propensity scores) with

those in the unregulated group, we find an increase in sales of the unregulated molecules in the matched subset of 28.7% compared to an increase of 17% for the regulated ones.

Since the unregulated molecules are affected by the regulation as well, they cannot serve as a credible counterfactual for the regulated ones. So to measure the impact of the regulation on the regulated molecules, we turn instead to a regression discontinuity (RD) design to measure the local average "treatment" effect of the regulation. This analysis further corroborates the previous findings – 25 regulated and 24 unregulated molecules show significant effects with former showing a negative effect on unit sales across most molecules and the latter a positive effect. A similar pattern of results is observed for rural prescriptions as well (18 regulated and 16 unregulated molecules show significant effects with former showing a negative effect across most and the latter a positive effect). Given the broad set of therapeutic categories associated with the regulated and the unregulated drugs, there is no obvious demand-side explanation for our findings. So we turn to the supply-side to investigate underlying reasons for our findings.

First, looking at the prices of the regulated and unregulated molecules, we see that while the prices of the former decline, those of the latter do not change. Thus lowered prices of the unregulated molecules cannot explain our findings. A plausible supply-side explanation is that the firms marketing the molecules shifted their efforts away from the regulated to the unregulated drugs. Unfortunately, data on marketing efforts are not available for all the molecules. Instead, we provide suggestive evidence using data from one specific company. While not generalizable to all molecules we consider, we find that this firm, facing smaller margins for the regulated drug, shifted its marketing efforts (detailing to physicians) away from that drug to an unregulated one resulting in the poorer (improved) performance of the regulated (unregulated) drug. Second, facing lower margins (DPCO reduced the retailer margins for the

regulated drugs from 20% to 16%) from regulated drugs, retailers reduced their orders and stocks of these drugs. While this could potentially affect our sales volume outcome measures it is unlikely to have affected our rural prescription behavior outcome measure. Although we find some anecdotal evidence of retailers stocking less in specific geographic markets, we note that ultimately, if physicians prescribe the drug, the retailer not stocking the drug will lose out to a competitor offering the product for sale.

2. Empirical Context

2.1 The Indian Pharmaceutical Market

The Indian pharmaceutical industry in 2015 was a $22 billion industry by revenues. The country is 3rd in the world in terms of the sales volume of medicines and 13th in terms of revenues. From humble beginnings in 1969, when 95% of medicines sold in India were sold by multinational pharmaceutical firms, Indian firms, subsequent to the promulgation of the process patent act in 1969, have reverse engineered many molecules and have grown to be known as suppliers of inexpensive medicines to the world. By the time a WTO (World Trade Organization) agreement to bring back product patents in India took effect in 2005, India had become home to the largest number of US Food and Drug Administration approved production plants in the world (Banerji 2013).

Unlike developed markets, 95% of medicine sales in India are of off-patent pharmaceutical molecules (known as generic drugs). Both unbranded generic molecules (eg. *Amoxycillin and Paracetamol*) and *branded* generic drugs (e.g., *Augmentin* - a branded *Amoxycillin*) are sold in India *with the branded generics being actively marketed by firms*. While the scale of the market in revenue terms is relatively small compared to developed markets, (for example, *Augmentin*, a branded generic antibiotic had annual sales of INR 2 billion (USD 28

million) in 2014), the volumes are substantial as prices in India are significantly lower than those in developed markets. As per capita income in India is low ($1800 in 2014), and neither universal healthcare nor universal insurance are available, cheaper generic alternatives to expensive medicines are widely available, which in turn, reduce the likelihood of high priced therapies launching successfully (Subramanian et al. 2014). Given low incomes, the lack of universal health care and privatized health care access, the Drug Price Control Order (DPCO) came into existence to fulfill a key policy goal of the Indian government - to provide increased access to medicines to people at affordable prices.

2.2 Prior Price Regulations in India

Prior to DPCO 2013, pharmaceutical price regulation in India has had a long history. The first DPCO was implemented in 1970, wherein the pre-tax profits from the pharmaceutical business of a firm were restricted to a maximum of 15% of revenues (Narayan 2007). However, prices and product-wise margins were under the control of firms. The DPCO was revised in 1979, 1987 and 1995. The 1979 DPCO brought 370 drugs under strict price control including many life-saving and essential medicines (termed 'category-1' drugs). With declining profits, many firms discontinued the formulations under price control. Realizing this issue, the 1987 DPCO reduced the number of drugs under regulation to 142. Further, the profit margins were also increased for these drugs. In 1995, the DPCO further liberalized the pharmaceutical industry by reducing the number of formulations under price control to just 74 (Narayan 2007).

Each of these DPCOs had a significant impact on the pharmaceutical industry. The profit margins trend in the industry (Figure1) reveals that there was significant decline post 1970. During the entire period from 1970 to 1994 (DPCO 1, 2 and 3), the margins were lower. However, the margins gained momentum post liberalization in 1995 (DPCO 4 in Figure 1).

Bellur et al. (1985) studied the reaction of pharmaceutical firms to the 1970 DPCO and found that several firms minimized the effects of the price regulation by shifting their focus to mass market, over-the-counter drugs and to other product categories (like animal health products). However, firms that were not already diversified into mass-market segments found it difficult to make a timely transition to high volume products. In short, "organizations which were well diversified - to cover the controlled and uncontrolled categories of product lines – will be in a more comfortable position than those operating in controlled categories only." (Bellur et al.1985, p.155). Price regulation shifted competition to other factors such as brand image and reputation. Further, the regulation also forced the firms to optimize their salesforce efforts and to be selective in their marketing efforts (eliminating unproductive rural and remote access areas).

[Insert Figure 1 here]

While the 1995 DPCO reduced the number of regulated molecules to 74, 27 of them are no longer under production, suggesting that manufacturers shifted their focus to unregulated molecules. Further, an IMS study on the effect of 1995 DPCO reveals that, contrary to the expected volume surge for the regulated molecules, volume growth stagnated in the following years (Mookim and Khanna 2015). However, related (unregulated) molecules experienced a surge in their volume sales growth.

2.3 Drug Price Control Order 2013

In May 2013, the Department of Pharmaceuticals (DoP) of India brought 348 specific formulations (molecules or combinations of molecules) under price control by the Drug Price Control Order (DPCO). The list of 348 medicines was taken from the National List of Essential Medicines (NLEM), which was compiled by the Ministry of Health and Family Welfare in 2011. These formulations are considered "essential and lifesaving drugs, and address the priority health

needs of the country." The objective of the DPCO 2013 was to ensure availability of essential medicines at affordable prices for the poorer masses, while still encouraging innovation and growth in the pharmaceutical industry (DPCO 2013). Further, the order authorized the National Pharmaceutical Pricing Authority (NPPA) of India to regulate medicine prices and monitor price increases of medicines that are not under regulation (Subramanian et al. 2014).

The price ceilings for regulated drugs were set using 'market-based' mechanisms. For most drugs, the price ceiling is the simple average of the prices of all brands in the market with market shares of at least 1%. Brands priced higher than this average reduced prices to at or below the ceiling, those priced below were to maintain their current price levels. If there is only one drug in a category, then the price is based on a fixed percentage derived from price reductions in similar categories. Annual price increases for the regulated molecules were restricted to be in line with or below the wholesale price index of India. *Unregulated molecules also were allowed a maximum price increase of 10% in any 1-year period*. The price ceiling set by the DPCO refers to the price to the retailer. The retailer margin is then fixed at 16%. While firms were allowed to exit from a given category with a six months' notice, the NPPA reserved the right to mandate continued production of up to 12 months (DPCO 2013).

DPCO 2013 represented a major turning point in the Indian pharmaceutical market. An independent study by Wan (2013) showed that molecules under DPCO 2013 account for about 60% of the pharmaceutical market in India and the order was expected to erode the value of the market by about $290 million annually (2.2% drop of the entire market). An IMS study compared the simple CAGR (cumulative annual growth rates) for a set of select few regulated and unregulated molecules and found that the growth rates for regulated molecules were

significantly lower than those for unregulated molecules (Mookim and Khanna 2015). Further, launches of new drugs declined from 270 drugs in 2008 to 56 in 2014 (FRPT-Research 2015).

3. Data

We obtained data from IMS Health (India) and SMSRC. Two types of data were obtained. First, we obtained monthly sales data; IMS primarily records data of sales from wholesaler to retailers. Our second data involve prescriptions in rural markets; we obtained the percentage of prescriptions of a drug written in rural areas. A vast majority of prescribers in rural areas do not have *allopathic* medical degrees and serve in low-income rural areas where healthcare access may be expensive even if available. These are doctors who specialize in *ayurvedic* or *homeopathic* medicine, but actively prescribe *allopathic* medicines as well; they represent about 16% of all allopathic doctors in the country (IMS Report 2013). Importantly, these doctors are detailed by pharmaceutical companies and are particularly dependent on such detailing for information about the various medications. Hence the fraction or prescriptions for a drug written by rural doctors represents the prescriptions that eventually serve the healthcare needs of the lowest income groups and the disadvantaged in the country, most of whom reside in the rural areas.

We are interested in examining the impact of the price control regulation on sales volume (overall and in lower tier cities) and on prescriptions in rural areas. While data on 105 drugs (oral solids) under price regulation are available in IMS, we assess the impact on 51 major oral solids ("regulated" molecules) that form about 90% of the total value of the 105 molecules (in terms of average sales value). We also select 57 molecules that are not under regulation ("unregulated" molecules), but are closely related to those under regulation, in terms of primary illnesses for

which the molecules are prescribed (for instance, we choose *Rosuvastatin* as the unregulated counterpart for *Atorvastatin* – both are typically prescribed for cholesterol control) [4].

Our outcome variables of interest are: i) monthly sales volume for each molecule, ii) percentage sales volume in lower tier cities[5] (henceforth, C24R%), and, iii) percentage prescriptions from rural doctors (henceforth, RuralRx%). The data are reported in monthly intervals. As each molecule has multiple SKUs (stock keeping units) depending on pack size and strength, we consider sales volumes of the largest selling SKU for each molecule as representative of that molecule[6]. For all these molecules (51 in the regulated group and 57 in the unregulated group), we collected five years of monthly sales data from May 2009 to June 2014, totaling 62 months (50 months before price regulation and 12 months post price regulation[7]). This ensures that we have enough variation to distinguish the effect of price regulation from other molecule specific factors. Further, for each of the 108 molecules, we collect information on C24R% and RuralRx%[8]. We also collect specific molecule properties that may influence the sales volume and prescription behaviors for drugs. These properties include – i) type of illness – acute vs. chronic, ii) primary indication (eg. *Atorvastatin* for cholesterol issues), and iii) percentage prescriptions by CP/GPs (consultant physician/general physician), indicating the type of doctors that typically prescribe the drug (henceforth, CPGPRx%) – for instance, *Imatinib*, a

[4] Molecules in the unregulated group were chosen based on the recommendations of two industry experts.
[5] IMS categorizes Indian cities into four groups – metro, class 1, class 2-4 and rural. We sum the percentage sales in class2-4 and rural to form C24R%.
[6] The largest selling SKU is typically the most prescribed strength and dose variation by physicians and specialists.
[7] DPCO did not allow any brand exits in the 6-month period after regulation (and reserved the right to mandate continued production for 12 months). Further, we did not find any brands with market share higher than 5% exit any of the categories (105 molecules) in the 12 months post regulation (a total of 6 brand exits were recorded, all with less than 5% market share in the period from Jan 2014 – June 2014). Further, as noted before, price increases for unregulated molecules were restricted to 10% in a 1-year period. Hence, we select 12 months as the time period for estimating the *ceteris paribus* effects of price regulation.
[8] Descriptive measures (in the pre-regulation and post-regulation periods) for all molecules used in the analysis are presented in Online Appendix 1.

medicine prescribed to cancer patients has on average 4.7% CPGPRx%, whereas *Oflaxacin*, an antibiotic has on average CPGPRx% of 75%.

We present the pattern of outcome variables in Figure 2 and the pre-regulation summary statistics in Table 1. Specifically, we present the average monthly values (50 months prior to price regulation) across the regulated and unregulated groups of molecules. In the pre-regulation period, the two groups are almost similar with some minor differences in their characteristics. The pre-regulation sales volume (sales units) is lower (but the difference is insignificant at 5% significance level) for the regulated group compared to the unregulated group. The molecules in the regulated group, on average, also have higher RuralRx% (difference=2.9%, $p<05$). Pre-regulation trends seem comparable across the regulated and unregulated groups (regulated molecules show more variability); we see a big impact of the regulation on rural prescriptions. Given the nature of the data and the timing of the regulation we are also able to control for differences in pre-regulation trends of the molecules, if any, as we discuss later.

[Insert Figure 2 and Table 1 here]

We also present some stylized facts from our data to illustrate how price regulation has influenced molecules in the regulated group compared to the unregulated group (Table 2). We find that, in the year after regulation compared with the period before regulation, sales increase by 8.8% in the regulated group, but there is a 34.1% increase in the unregulated group. Prima-facie, one might misinterpret the 8.8% increase as evidence that the regulation is working. However, from Figure 2 we see that there are trends and seasonality in the data that need to be accounted for in our analysis. With the exception of C24R%, the shift is significantly negative ($p<.05$) across all factors. The shifts (column titled 'Difference' in Table 2) represent the difference-in-difference values (post-regulation and pre-regulation values are differenced for all

molecules, and these differences are compared between the regulated and unregulated groups). The negative difference-in-difference values indicate that the regulated molecules may have been negatively impacted vis-à-vis the unregulated ones in terms of overall sales volume and RuralRx%.

[Insert Table 2 here]

4. Empirical Framework and Identification Strategy

We are interested in learning how price regulation has an effect on sales volume (units), percentage of sales in lower tier cities and percentage of prescriptions in rural areas for the regulated and closely related unregulated molecules. Each of these measures provides different information and insights to marketers and policymakers. An ideal experiment to estimate the effects of price regulation is to randomly select a set of molecules and regulate their prices. Then we can examine the effect of price regulation for these molecules against a randomly selected set of control molecules, that are completely unaffected by the price regulation. However such an experiment is not feasible for several reasons.

i) The decision to include a molecule under the regulation is not random for the regulated group. Indeed, the GoI focused on these drugs due to their essential and lifesaving nature.

ii) Since companies manage a portfolio of products, they may have shifted marketing efforts to the drugs in their portfolios that belonged to the unregulated group. This might be motivated by the potentially more lucrative nature of those drugs since they were not subject to the regulation. This renders the unregulated group unfit to be a credible counterfactual for the regulated group.

A credible control group would be a set of molecules that are similar to those under regulation, but are completely unaffected by the regulation intervention. The alternative option is to identify molecules that are completely unrelated to the molecules under regulation. However,

the regulated molecules are considered essential medicines (taken from NLEM) addressing key indications. A control group composed of molecules addressing other indications and are unaffected by regulation, would, once again, not be a credible counterfactual, as the group would be systematically different from the regulated molecules. Thus even if we could design a controlled experiment to evaluate the impact of the regulation, it is unclear how such an experiment can be implemented. To ensure identification of the effect of price regulation therefore, we adopt multiple methods that, we hope, collectively address each of these concerns.

4.1 Panel Fixed-Effects Regression

We begin our analyses with a simple panel fixed-effects regression, which enables us to account for molecule and indication specific time-invariant factors, trends and other features in the estimation. If molecule fixed effects account for factors that determine why a molecule was "selected" into the regulated group, and if the *timing* of the regulation can be treated as random (since it occurs at the same time across molecules and so molecules cannot "self-select" into the treatment at different strategic times), then the panel fixed-effects estimator can provide us with a useful base case regarding the impact of the regulation. Having access to detailed molecule-level information allows us to control for a number of confounding factors. For example, a given molecule may be appropriate for multiple indications. Hence, we need to account for demand shocks specific to this molecule. Consequently, we include a number of fixed effects – month fixed-effects to account for seasonality, molecule, year, and molecule-year interactions to account for the selection of molecules into the regulated list and for differential trends in the sales of the different molecules. We begin by estimating the average effect of price regulation in the two groups. We estimate the following panel regression:

$$Y_{it} = \beta_0 + \beta_1 PostReg_t + \beta_2 (IsNLEM_i * PostReg)_{it} + X^l{}_{it}\beta + FixedEffects + \varepsilon_{it} \qquad (1)$$

where i = 1,..108 molecules, t= 1,..62 (panel time period: 1 – May 2009 and 62 – June 2014), Y_{it} refers to the outcome variable of interest, $PostReg_t$ takes the value of 0 from May 2009 to June 2013 (pre-regulation period) and takes the value of 1 from July 2013 to June 2014 (post-regulation period), $IsNLEM_i$ takes the value of 1 if molecule i belongs to the regulated group or 0 otherwise , X^l_{it} is the set of covariates representing time-varying molecule characteristic and *FixedEffects* refers to the various fixed-effects that we include in the analysis. We add the following fixed-effects to the model – i) molecule, ii) month, iii) year, and iv) molecule-year interactions[9]. The coefficients of interest are β_1 (coefficient of *PostReg*) and β_2 (coefficient of *IsNLEM * PostReg*). The coefficient β_1 indicates the average effect of regulation across all molecules (in both unregulated and regulated groups) in the period after regulation. The coefficient β_2 captures the average difference in the outcome variable between the regulated and unregulated groups in the post-regulation period.

4.2 Propensity Score Matching

As we see from Table 1, the two groups (regulated and unregulated) differ in their pre-regulation levels of sales (though insignificant) and rural prescriptions. Hence, we employ propensity score matching to address the issue of non-comparability of regulated molecules and the closely related unregulated molecules. A matching estimator compares the outcomes of a regulated group and unregulated group, where the two groups are 'matched' based on similarity on observables (Smith and Todd 2008). The method addresses a key issue of linear regression – the assumption of a functional form for controlling observables. Matching estimators allow for a non-parametric flexible relationship for observables (see e.g., Goldfarb and Tucker 2014).

[9] As a robustness test, we also included molecule specific polynomial (order 3) time trends (not fixed-effects) defined at the monthly level (results in Online Appendix 2).

Specifically, we use the following variables averaged over the pre-regulation period to compute propensity scores: log (sales), C24R%, RuralRx% and CPGPRx%. This process provides a matched sample – molecules that are similar in terms of the observable features in the pre-regulation period with equal propensities of being chosen for regulation. With this matched sample, we estimate the impact of price regulation on outcome variables using the panel regression model explained in Equation (1). We argue that, given the similar pre-regulation values in the two groups, the observed differences post-regulation may be attributed to price regulation. This enables us to account for the bias introduced by the non-comparability of the two groups and estimate the average effect of regulation on regulated and unregulated molecules.

4.3 Regression Discontinuity Design

Matching, however, does not address the primary challenge for identification - lack of a credible counterfactual or control group. Hence, there may be unobserved factors that are changing over time, as both the groups are affected by the regulation intervention. The concern with estimating Equation (1) using fixed-effects panel regression is that these unobserved factors may produce biased estimates of β_1 and β_2. We therefore, use a regression discontinuity (RD) design to address this identification issue. The RD design works on the principle that assignment to a treatment condition is determined by the value of a predictor variable. Treatment is assigned only when the predictor is above a particular fixed threshold, creating a discontinuity at the threshold if the treatment effect is significant (Imbens and Lemieux 2008). In our case, the effective source of the regression discontinuity is time. Under the assumption that the threshold is random and not associated with underlying outcome discontinuities, any discontinuity can then be attributed to the treatment (Hartmann et al. 2011). The RD design addresses the endogeneity issue by considering a narrow window of time around the implementation of price regulation.

Within this interval, the unobserved factors influencing the outcomes are likely to be similar so that observations just before regulation provide a comparison group for observations just after regulation. In other words, *after adjusting for time trends*, the outcomes just before and just after regulation should not be different, as the policy intervention is external to the outcome trends of the molecules. Any discontinuity in the regression may then be attributed to the price regulation intervention. Specifically, we examine whether there is a discontinuity in the trend of outcomes for each of the molecules around the intervention period (July 2013), and test for direction and significance of this change.

For assessing the effects of regulation, we consider price regulation as the binary intervention or treatment. Time (month) is the underlying running (predictor) variable and the intervention is applied when regulation is implemented in July 2013. Hence, July 2013 acts as the cut-off point for the RD design. Let $Y_{it}(0)$ and $Y_{it}(1)$ denote the pair of outcomes for a molecule i at time t: $Y_{it}(0)$ is the outcome without exposure to price regulation and $Y_{it}(1)$ is the outcome after price regulation. Hence our focus is on $Y_{it}(1) - Y_{it}(0)$. However, we do not observe both $Y_{it}(0)$ and $Y_{it}(1)$ together. We use the RD design to focus on (local) average regulation ("treatment") effects. The rationale behind RD design is that the treatment (in this case price regulation) is determined partly (warrants fuzzy RD design) or completely (warrants sharp RD design) by the predictor variable. As the intervention is at a specific time t (deterministic function for assigning treatment), we use the sharp RD design. Any discontinuity of the conditional distribution of the outcome around the cut-off point (July 2013) may be interpreted as the causal effect of price regulation. Let the deterministic function be $W_{it} \in \{0,1\}$ such that W_{it} takes the value of 1 when $t>c$ (in our dataset, when t=50, regulation is implemented, and hence c=50 and W_{it} takes the value of 1 when $t>50$) and 0, otherwise. In the sharp RD design, we

examine the discontinuity of the conditional distribution of the outcome given the regulation at the cut-off point, to identify the average treatment effect:

$$\tau_{SRD} = \mathrm{E}[Y_{it}(1) - Y_{it}(0)|W_i = 1] \quad (2)$$

where τ_{SRD} refers to the LATE (local average treatment effect) estimate. The bandwidth over which the LATE is estimated is identified using the Imbens-Kalyanaraman optimal bandwidth calculation (Imbens and Kalyanaraman 2012). As the RD design is specific to each molecule, the average treatment effect estimated is specific to each molecule. In other words, while RD designs provide very high internal validity, the results may not be generalized to other subpopulations of molecules (Imbens and Lemieux 2008).

The RD coefficients are molecule-specific (dependent on scale of outcomes). Hence average LATE may not be an appropriate aggregate measure of regulation effect. We use the RD coefficients, the bandwidths identified using Imbens-Kalyanaraman method and the standard deviation scores around the bandwidths, to compute the effect size and variance for each molecule. As we are looking at mean change around the cut-off point (outcomes just before and just after the regulation are expected to be equal in case of null effect of regulation), the effect size is the standardized mean change computed using raw score standardization allowing heteroscadastic variances before and after regulation (Bonnet 2008). Once we compute the effect sizes and variances for all molecules, we apply the standard meta-analysis methodology (Schmidt and Hunter 2014) and employ restricted maximum likelihood (random-effects) (Viechtbauer 2005) to estimate the overall weighted effect size. We expect the weighted effect size to be negative for regulated and positive for the unregulated group.

4.4 SARIMA Forecasting of Post-regulation Sales Using Pre-regulation Data

Finally, to provide additional evidence, using the pre-regulation data of all the molecules, we fit a forecast function and create a credible counterfactual for each molecule in the post regulation period. The difference between the forecast and the actual values post-regulation indicates whether regulation has resulted in an increase (decrease) in outcomes. We follow three stages: i) estimate a SARIMA (seasonal autoregressive integrated moving average) function (with or without drift) using historic sales (pre-regulation) data, ii) create a baseline using the forecast function for the period immediately following the regulation (12 months) and, iii) compare the actual outcomes with the baseline to isolate the average effect of regulation. In other words, we estimate the residuals of the forecast function for the period following the regulation and test for direction and statistical significance.

We identify the best fitting seasonal ARIMA model using the algorithm developed by Hyndman and Khandakar (2008). We identify an ARIMA (*p, d, q*) (*P, D, Q*) [m] model where *p* and *q* refer to the autoregressive and moving average models respectively, *d* refers to the degree of differencing, *P*, *D* and *Q* refer to the autoregressive, differencing and moving average terms of the seasonal component of the model and *m* refers to the length of seasonality (eg. 12 months in one year). The specification of the seasonal ARIMA (*p, d, q*) (*P, D, Q*) [m] process is presented in Equation (3).

$$\Phi(B^m)\,\phi(B)\,(1-B^m)^D(1-B)^d y_t = c + \Theta(B^m)\theta(B)\varepsilon_t \qquad (3)$$

where $\Phi(z)$ and $\Theta(z)$ are polynomials of orders *P* and *Q* respectively (both contain no roots in the unit circle), $\phi(z)$ and $\theta(z)$ are polynomials of order *p* and *q* respectively (both have no roots for |z| <1), *c* is the drift term and if c ≠ 0, then it implies a polynomial of order *d* + *D* in (1). B refers to the backshift operator, ε_t denotes the white noise process and $y_t$refers to the time indexed percentage sales growth. An overview of the algorithm followed (Hyndman and

Khandakar 2008) to fit the seasonal ARIMA model (identify the appropriate *p, d, q, P, D* and *Q*) is explained below:

1. The value of *D* is first chosen based on Canova-Hansen (1995) test. This test checks whether the seasonal pattern changes significantly over time to warrant a seasonal unit root.
2. The value of *d* is chosen by using successive KPSS (Kwiatkowski et al. 1992) unit root tests. The test is applied on seasonally differenced data if $D \neq 0$ and on original data if $D = 0$.
3. If $d + D < 2$, then the drift term *c* is included in the model.
4. A step-wise algorithm is then used to evaluate different models (for detailed steps of the algorithm refer Hyndman and Khandakar 2008, p.11).
5. The values of *p, q, P* and *Q* are chosen by minimizing the AIC (Akaike Information Criteria).

We identify the best fitting models for the regulated and unregulated molecules. The objective is to get the best fitting forecast function based on AIC (Akaike Information Criteria) and robustness of the model was verified using MASE[10] (mean absolute scaled errors) (Hyndman and Koehler 2006, Kostenko and Hyndman 2008). Specifically, we verify that the MASE of the forecast functions are below one (for a detailed discussion, refer Franses 2016). Using the models identified from historic data (pre-regulation), we forecast the outcomes from July 2013 to June 2014 (post-regulation period of 12 months). We compute the differences between the forecasts and actual values (residuals) and test for significance. A significant difference between the actual and the predicted outcomes may then be attributed to price regulation. We expect the results to be consistent with those obtained from RD approach.

5. Results

5.1 Panel Estimation

[10] MASE, as the name indicates, is independent of the scale of the data and allows the forecast accuracy to be compared over several molecules with different scales. MASE values greater than one indicate that the one-step naïve forecasts perform better than the forecast function.

We estimate the average outcome effects of price regulation on regulated and unregulated (closely related) molecules using the fixed-effects panel model explained in Equation (1). The results of the panel regression models with i) log (sales volume), ii) log (C24R%), and iii) log (RuralRx%) as the dependent variables are presented in Table 3 (complete analysis results for each of the dependent variables are presented in Online Appendix 2)[11]. In the case of sales volume, the coefficients of *PostReg* (β_1=.053, p<.05) and *IsNLEM*PostReg* (β_2=-.090, p<.05) are significant, indicating that sales increased for the unregulated group but declined for the regulated group. The unregulated group had an average increase of 5.3% sales volume in the post-regulation period. However, the regulated group had an average decline of 3.7% (sum of β_1 and β_2). We find that both the regulated and unregulated groups had an average increase of 3.4% (β_1=.034, p<.05) in C24R% post-regulation. The effect of the interaction term (β_2) is not statistically significantly different from 0 at the 5% level indicating no differences between the regulated and unregulated groups in the post-regulation period. Given the overall decline in sales volume of the regulated, this indicates that the absolute level of sales in these markets declined in regulated group relative to the unregulated group. Finally, RuralRx% of the regulated molecules declined on average by 18.7% while the unregulated molecules saw an average increase of 8.6% in the 12 months following regulation.

5.2 Matching Estimators

As there are some minor differences between the regulated and unregulated groups in the pre-regulation period, we adopt a matching procedure to address the issue of non-comparability of the groups. We use the following covariates averaged over the pre-regulation period to compute the propensity score of being in the regulated group: log (sales), C24R%, RuralRx%

[11] For the dependent variables in ii) and iii) we also estimated logistic regressions with log(y/1-y) as the dependent variable (results in Online Appendix 2) and the results are consistent.

and CPGPRx%. We use a probit model for computing propensity scores and apply a caliper of .01 for the propensity scores. The balance of the covariates in the regulated and unregulated groups after matching is presented in Online Appendix 3. After matching, we have 1,798 observations (number of regulated molecules, $N_{regulated}$= 13 and unregulated molecules, $N_{unregulated}$= 16). With the matched sample, we re-estimate the coefficients of the panel model in Equation (1) with log (sales), log(C24R%) and log(RuralRx%) as the dependent variables (similar to Tsai et al. 2015). Results of the analyses using the matched sample are presented in Table 3. Consistent with our earlier estimates, after regulation, relative to the unregulated group, the regulated group has 11.7% lower increase in sales volume ($p<.05$) and 7.4 % ($p<.05$) fewer prescriptions from rural doctors. Additionally, we find the effect of regulation on the lower tier cities in the regulated group to be negative (β_2=-1.2 %, $p<.05$) relative to the unregulated group, in the period following price regulation.

[Insert Table 3 here]

5.3 Regression Discontinuity Design

To address the issue of lack of credible counterfactuals for the regulated group (as the unregulated group is also affected by price regulation), we use RD design to examine whether there is a discontinuity in the outcomes for the molecules around the period of regulation. While the results of RD designs may not be generalizable to other molecules, the results have high internal validity at the molecule level. We estimate the RD coefficients or local average treatment effects (LATE) for each molecule as specified in Equation (3), while accounting for time trends. We use a sharp RD design at the July 2013 cut-off (month of implementation of price regulation). The bandwidths (on either side of the threshold) are computed using the Imbens-Kalyanaraman optimal bandwidth calculation (Imbens and Kalyanaraman 2012). We use

a ‘triangular’ kernel to be used in the local linear fitting as specified by Lee and Lemieux (2010). We conduct RD estimation for each of the regulated and unregulated molecules, with the bandwidths being identified separately for each molecule. The detailed results of RD estimations for the three outcome variables are presented in Online Appendix 4.

With log(sales) as the outcome variable, we find that the RD coefficients are significant for 25 regulated molecules and 24 unregulated molecules. We compute the average LATE estimates (results presented in Table 4 and illustrated in Figure 3) for the regulated and unregulated molecules. Overall, the average LATE of unregulated molecules (24 molecules with significant LATE) is found to be .071 whereas the average LATE of regulated molecules is -.064 (25 molecules). We find a similar pattern of results for log(RuralRx%); the average LATE estimate of log(RuralRx%) is .033 (16 molecules with significant RD coefficients) for unregulated molecules, and -.051 (18 molecules with significant RD coefficients) for regulated molecules. Further, majority of LATE estimates were insignificant for log(C24R%) – only 4 unregulated molecules (average=.028) and 7 regulated molecules (average=-.011) have significant RD coefficients. Overall, the list of specific molecules with significant LATE are slightly different (there is significant overlap) for the log(sales) and log(RuralRx%).

[Insert Figure 3 here]

As the RD coefficients are molecule-specific, aggregating the LATE values may not provide interpretable results. We compute pre- and post-regulation standard deviations of outcomes for each molecule over the bandwidths identified from the Imbens-Kalyanaraman method. The pooled standard deviation (Olejnik and Algina 2000) is then computed for estimating the effect size of the LATE measures. The RD coefficients and the pooled standard deviations are used to estimate the standardized mean change (allowing for heteroscadistic

variances before and after regulation) (Bonnet 2008). The weighted effect size (Schmidt and Hunter 2014; Viechtbauer 2005) for regulated and unregulated molecules are presented in Table 4 for the three outcome measures. We first compute overall effect size of all molecules (plots with effect sizes and confidence intervals for all molecules are in Online Appendix 4) and then with just the molecules with significant RD coefficients. In the case of log(sales), the effect size (using random-effects, restricted maximum likelihood estimator) is found to be -.354 ($p<.05$) for the regulated group, compared to .139 ($p<.05$) for the unregulated group. Further, we compute the 'fail-safe' metric using the Rosenthal method. Fail-safe number indicates the number of molecules with null results in order to render the overall weighted effect size to be insignificant (Rosenthal 1979). The fail-safe number for the regulated molecules is found to be 3,187 (significantly higher than the total number of molecules under regulation), whereas the fail-safe for unregulated molecules is found to be 1,721. Overall results suggest a decline in sales volume for regulated molecules, while the sales volume of unregulated molecules, on average increased. Similar pattern of results are observed for log(RuralRx%). However, in case of log(C24R%), the effect size is positive and marginally significant (.129, $p<.10$) for the unregulated group, while it is insignificant for the regulated group.

[Insert Table 4 here]

5.4 Forecast Outcomes

Using Hyndman and Khandakar's (2008) algorithm, we identify the best fitting SARIMA models for all the molecules. The models are fit to the pre-regulation data and are then used to forecast for 12 months after regulation. Next, the differences between actual outcomes and forecast values are tested for significance. For each molecule *i*, we compute the average of these differences in the *post-regulation period*, termed the 'average treatment' effect ($ATE_{actual\text{-}forecast}$)

$$ATE_{i(actual-forecast)} = Avg\big(ln(actual_i)\big) - Avg\big(ln(forecast_i)\big) \quad (4)$$

The magnitude of LATE estimates (effect sizes) and $ATE_{actual\text{-}forecast}$ are not directly comparable. However, when there is a significant discontinuity at the point of intervention, we expect the direction of $ATE_{actual\text{-}forecast}$ to be consistent with that of LATE estimates, providing additional evidence. Hence we expect the ATE values to be significant for molecules with significant LATE estimates. Overall pattern of results are consistent with that of RD design results with some exceptions (majority of the molecules with insignificant LATE estimates, also have insignificant ATE values). Table 4 reports the results for the three outcomes[12] (summary results for molecules with significant LATE estimates).

5.5 Robustness Checks

We find that the pattern of our reported results are robust to the following additional tests albeit with minor exceptions.

5.5.1. Timeline. As the announcement for price regulation was made in May 2013 (giving the firms, 45 days to comply with the new prices), we drop May and June 2013 data and redo the analysis. Our findings are robust to whether the data on two months are included. For instance, in the case of log(sales), when we drop 2 months from our analysis, the evidence is stronger for the negative effect on regulated molecules (31 molecules with significant LATE, majority being negative) and positive effect on unregulated molecules (30 molecules with significant LATE, majority being positive).

5.5.2. Matching Estimators. We check the sensitivity of our results to different caliper values (.01 and .001) in identifying the matched sample. Next, we also conduct coarsened

[12] ATE values for the three outcome variables (all molecules) are presented in Online Appendix 4.

matching with the covariates, to assess the similarity of the matched sample obtained. The selection of matched sample was robust to different criteria and matching methods.

5.5.3 Regression Discontinuity Design. In the earlier reported results, bandwidths were computed for each of the molecules to estimate RD coefficients. As a robustness test, we double the Imbens-Kalyanaraman bandwidth to assess the sensitivity of the results to bandwidth selection and find the results to be consistent.

Next, we conduct 'placebo' RD tests by assigning the cut-off point at two different pre-regulation periods (20 months and 35 months in the pre-regulation period), and once in the post-regulation period (6 months after regulation), and find no significant discontinuities with minor exceptions for molecules with significant LATE estimates[13]. We also conduct a placebo test 30 months into the pre-regulation period when NLEM list was first announced (September 2011) and find that the announcement did not have a significant impact on sales and prescription behavior (detailed results in Online Appendix 5).

5.5.4 Forecast Function. To assess the sensitivity of our results to prediction errors, we split the pre-regulation period (50 months) into two halves for the molecules with significant ATE values, use the first 25 data points to forecast for the next 12 periods. While the forecasts were found to be significant, the residuals (difference between actual and forecast values in the post-estimation period) were mostly insignificant, for the three outcome measures. This indicates that absence of a discontinuity after 25 months as the model from the first 25 months was able to predict sales from the next 25 whereas the earlier results indicated the presence of a discontinuity when the regulation went into effect.

6. Mechanism

[13] While we conduct placebo tests for all molecules, for brevity, we only report the results for molecules with significant RD estimates in Online Appendix 5.

Prior research provides evidence that pharmaceutical price regulation may result in declining pre-tax profit margins to companies (Vernon 2003; Vernon et al. 2006). Further, prior regulations also reveal a significant decline in profit margins in India (refer Figure 1). Regulated molecules may become unattractive to firms for two reasons – i) regulated price is relatively lower compared to other molecules in the firm's portfolio, and ii) high percentage reduction in prices after regulation. The relationship between regulated prices, weighted percentage price reduction[14] and LATE estimates for the 25 regulated molecules with significant RD coefficients, is presented in Figures 4a and 4b (details in Online Appendix 6). The LATE estimates appear to be positively correlated (even after dropping an outlier) with regulated prices (higher the regulated price, lower the negative value of LATE). Further, the LATE estimates are negatively correlated with percentage price reduction, which suggests that higher price reductions are associated with higher negative values of LATE. This provides evidence that higher negative discontinuities are observed when regulated prices are lower or when the percentage reduction in prices are higher or both.

[Insert Figure 4 here]

While the price control order brought a ceiling on price increases for the unregulated drugs, the firms are not required to reduce their current prices of these drugs. Hence, the profit margins on unregulated molecules are preserved (if firms do not decrease the prices of unregulated molecules), while the margins for the regulated molecules declined due to reduction in prices. We compute simple average prices of unregulated molecules (with significant LATE estimates) just before regulation (March 2013), just after regulation (June 2013) and 6 months post-regulation (December 2013) (details in Online Appendix 6). We find that there are no major

[14] We take the top 5 brands for each molecule (based on market share) and compute a weighted average reduction (with market shares as weights) in prices.

price decreases (average price decreased only for 3 molecules in June 2013 and for 2 molecules in December 2013). Hence, we can eliminate decline in prices as the potential explanation for the increase in sales of unregulated molecules. However, lower margins for the regulated drugs seem to have done 2 things – lowered the motivation of manufacturers to detail the drugs and lowered the motivation of retailers to stock the drugs.

In the pharmaceutical industry in India where DTC advertising for prescription drugs is illegal, companies rely on detailing as the main promotion vehicle to compete for prescriptions from physicians. Detailing refers to a firm's salesforce effort in terms of interaction with the physicians to provide information about the company's brands for various molecules (Manchanda and Chintagunta 2004). When the profit margins decline for a brand, a possible reaction from a firm could be to shift the detailing efforts to more profitable brands. This would mean, reducing the overall number of visits required for a particular brand (at the national level) by the firm's salesforce. We provide suggestive evidence for the proposed mechanism using detailing data for two brands (one regulated and other unregulated) from a top pharmaceutical firm in the country. The brands chosen for this analysis are represented[15] as Brand R (regulated molecule) and Brand UR (unregulated molecule). Both these brands are typically prescribed for cardiac issues (heart disease or hypertension) and are considered close substitutes[16]. The firm headquarters plans the total number of visits (termed as exposures) to be covered by its salesforce for each brand on a monthly basis. The number of visits are computed for – i) new doctors, ii) non-core doctors (these doctors are visited only once in a month), and iii) core doctors (more than one visit per month). Using data (from April 2012 to June 2014 -15 months

[15] We disguise the names of the brands to protect the anonymity of the pharmaceutical firm that shared the data (at the firm's request).
[16] While the price of Brand UR was unchanged, the firm had to reduce the price of Brand R, after regulation.

of pre-regulation and 12-months of post-regulation data) for the two brands, we provide evidence of shift in detailing efforts that can be attributed to price regulation.

Our main outcome variables of interest include, i) log(visits), and ii) log(sales volume). We use a RD design to identify any discontinuities (with July 2013 as the cut-off), *after accounting for time trends*. Results of the analysis (Table 5) indicate that there is a significant discontinuity revealing negative LATE for Brand R and positive LATE for Brand UR, across the two main outcome variables (RD figures presented in Figure 5). Further, the RD estimates across the three categories of visits reveal changes in the distribution of detailing efforts. LATE estimates for new doctor visits are positive for both Brands R and UR. However, the non-core and core visits have a negative LATE for Brand R, indicating a decline in detailing plan for the regulated molecule (RD figures in Online Appendix 7). In the case of Brand UR, the LATE for core visits is found to be positive and significant. Our results indicate that the firm has increased the number of new doctors to be visited (across all molecules) post regulation, increased the detailing for core visits for Brand UR (to gain market share for the unregulated molecule) and decreased both core and non-core visits for Brand R (as a result of decline in profit margins).[17] Overall, our results indicate lower detailing efforts for the regulated molecule accompanied by lower sales in the post-regulation period.

[Insert Table 5 here]

The above rationale for the findings was confirmed when a top management executive and strategy team members in the firm were interviewed. The interviews also revealed that firms were mostly unwilling to reduce the prices of unregulated molecules, as such a reduction would

[17] An alternative approach would be to control for the detailing levels in the analysis. This would predict that the post-regulation dummy interacted with whether the molecule was regulated would no longer be statistically significant. While we find this to be the case, we prefer the current approach since (a) our objective is only to identify the mechanism; and (b) including time-varying detailing levels raises the issue of endogeneity.

have an effect on all future price increases (as price increases for unregulated molecules were restricted to 10% in one year). Further, the interviews revealed that rural doctors typically fall under non-core visits (one visit per month) and post-regulation, in many regions detailing efforts were reduced for rural doctors for the regulated molecules. One of the reasons cited is the cost associated with access to remote rural areas. As noted previously, majority of the rural doctors do not have formal *allopathic* medical degrees and depend on detailing for medical information. Reducing detailing to these doctors therefore has a big effect on rural prescriptions. Overall, we find the firm's actions to be consistent with our arguments and results.

Another potential explanation of lower sales for regulated drugs is that the retailers may stock less of the regulated drugs due to lower margins. DPCO 2013 fixed the retailer margin for the regulated molecules at 16%, whereas the average retailer margin for the unregulated molecules is around 20% (Mukherjee 2013). Hence there is an incentive for retailers to sell less of the regulated drugs. Note that this could potentially explain our sales outcome measures but is unlikely to have influenced our third outcome measure – the percentage of prescriptions written in rural markets (at least in the immediate aftermath of the regulation). Press reports suggest that wholesalers and retailers insisted on the old margins so pharmaceutical firms had no option but to sell to the channel at low prices (Unnikrishnan and Unnikrishnan 2014), cutting down their own margins given the price cap on MRP. As a result, 65% of the pharmaceutical firms restored older trade margins (Vaitheesvaran 2013). This led to further lowering of manufacturer margins, thus resulting in even lower motivation to detail.

7. Conclusions

We examined the effect of price regulation on a set of regulated and closely related unregulated molecules on three outcome variables – i) sales volume, ii) percentage sales in lower

tier cities, and iii) percentage prescriptions from rural doctors. In the case of sales volume, regression discontinuity design results indicate that 25 (of the 51) regulated molecules have significant discontinuities when the regulation was implemented, with majority (19) experiencing a negative impact. Contrary to the policy objectives, the regulation has resulted in lower sales volume in spite of price reduction. However, results also suggest discontinuities for 24 closely related unregulated molecules with majority (22) being positive.

We did not find any significant differences in terms of percentage sales in lower tier cities (the change in sales volume for the regulated molecules and unregulated molecules, are similar across higher and lower tier cities). Finally, we find that percentage prescriptions from rural doctors significantly declined for regulated molecules (14 molecules with negative LATE and 4 molecules with positive LATE – overall weighted effect being negative) whereas, that of unregulated molecules increased (14 molecules with positive LATE and 2 molecules with negative LATE – overall weighted effect being positive).

We provide suggestive evidence that the shift in sales and prescriptions from remote and rural areas may be attributed to the shift in detailing efforts of firms. First, we find that the regulated price and weighted percentage price reduction of the regulated molecules were correlated with LATE estimates obtained from RD analysis. This indicates that the lower priced and high price-reduced regulated molecules were less attractive for firms. Second, using two specific brands (one regulated molecule and another unregulated molecule), we find a shift in detailing efforts and sales volumes. Specifically, there is a negative discontinuity in the number of visits (for detailing) planned by the firm headquarters for the regulated brand whereas the discontinuity was positive for the unregulated brand (from the same therapeutic class). A similar pattern of results was observed for the sales volume of the two brands. We also find that the

detailing efforts were specifically reduced (increased) for core doctors (doctors who are visited more than once in a month for detailing) for the regulated (unregulated) brand. Finally, interviews with industry personnel revealed the strategic shift of detailing in remote access rural areas. Due to the unproductive nature of detailing for regulated brands (with reduced margins), detailing in these regions was restricted.

Prescription drugs (both regulated and unregulated) in India are among the lowest priced in the world (even prior to regulation). The prices are almost 65% lower than the country's BRICS counterparts (Mookim and Khanna 2015). Hence reducing the price ceilings via regulation adversely affects the profit margins. Currently, the price regulation targets the supply-side of the market by controlling manufacturer prices and their margins. However, as our results indicate, marketing incentives have been reduced (as evidenced by reduction of detailing efforts by manufacturers) and the market has shifted to more profitable alternatives within the same therapeutic class (Liepina 2011), resulting in a demand-side shift. Firms may also evade the price ceiling by adding or changing the formulations of the drugs under regulation (e.g. focus on marketing *Atenolol/Amlodipine* combination instead of the separate molecules that are under price control). In the long term, the firms may completely stop making the drugs under control and migrate to other molecules in the same therapeutic class, rendering the price control ineffective, as observed in DPCO 1995 (25 of 74 regulated molecules are no longer produced).

In concluding, our main takeaway for regulators is to consider the entire system – patients, doctors, and firms when considering such regulations. If physicians are dependent on pharmaceutical reps for their information on drugs (especially primary care physicians who have to prescribe across a very broad range of therapeutic categories), then price regulation could be susceptible to firms redirecting their marketing efforts towards more lucrative drugs and

categories. Alternatively the regulator may consider focusing on a few key categories while extending the price ceiling to all molecules in that category. Nevertheless, our study does point to potential unintended consequences of good intentions on the part of the regulator.

We would also like to acknowledge several limitations of our study. First, though the regulated and unregulated molecules are closely related substitutes, the molecules in the two groups may differ in term of severity of indications in driving prescriptions. For instance, *Atenolol/Amlodipine* combination (unregulated) may be prescribed for the additive benefits in case of severe hypertension as opposed to *Amlodipine* (regulated) alone. Second, only a subset of our chosen regulated molecules has significant negative LATE estimates. Further research may explore the reason for the remaining regulated molecules that seem to be unaffected by regulation. Third, while RD designs ensure high internal validity for the molecules examined, the results may not be generalizable. While the meta-analysis and fail-safe metrics provide some evidence for generalizing the RD results, further research may focus on broadening our conclusions beyond those considered. Fourth, we only estimate the effects of regulation over a 12-month period post regulation. Further research may explore long-term changes in detailing efforts, prescription behaviors and sales volumes. Further, in our post-regulation analysis period (12 months), there are no significant brand exits from the categories under price control. However, in the long-term, brand exits may be high and further research may focus on assessing the impact of price regulation on brand exits and brand entries into the (un)regulated categories. Fifth, our units of analysis are the molecules. Further research can examine the effect of extent of price reduction for brands (as few brands had to reduce prices to the market average, while others had to maintain their current prices) on market share for those brands. This would provide additional evidence at the brand level that firms were shifting their marketing efforts to other

brands in the portfolio. Finally, in the pre-regulation period, though there is no regulation, the level of competition for each molecule may be different. This may essentially have an impact on how firms react to regulation. Further research may examine any structural changes in competition post-regulation in the pharmaceutical domain.

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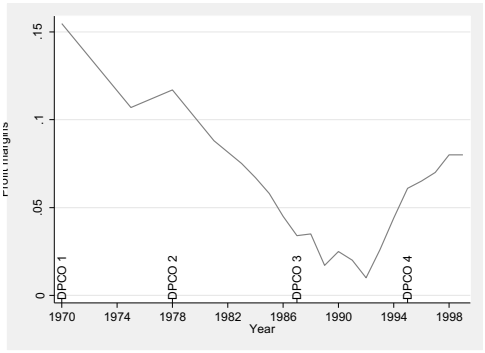
Figure 1 Profit margin trends (1970-2000)

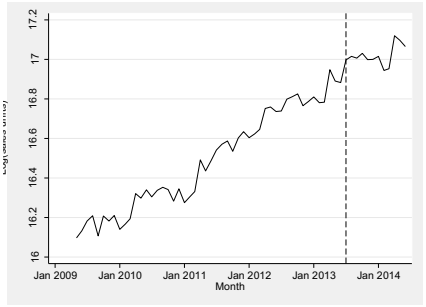


(Data source: IndiaIndustryStat.com)

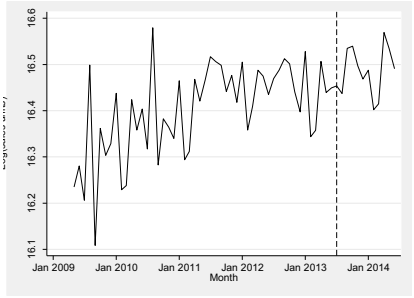
Figure 2 Outcome raw data patterns before and after regulation

Outcome variable: Average of log(sales units)

a. Unregulated molecules

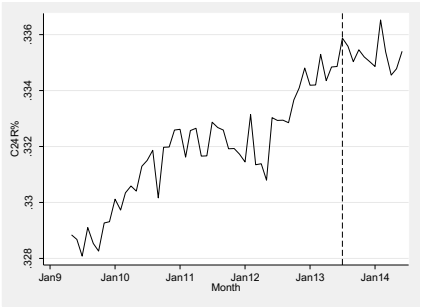


b. Regulated molecules

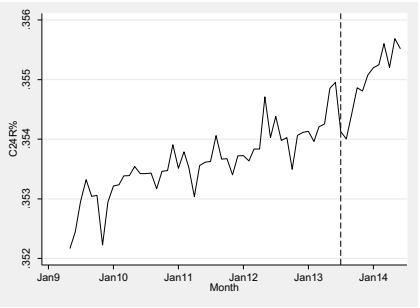


Outcome variable: Average of C24R%

c. Unregulated molecules

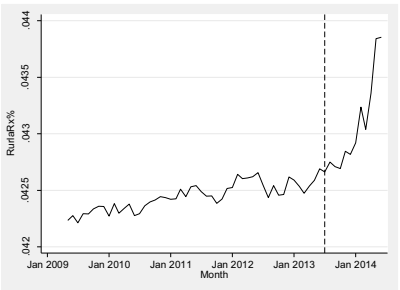


d. Regulated molecules

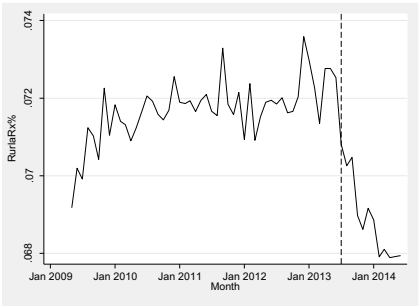


Outcome variable: Average of RuralRx%

e. Unregulated molecules



f. Regulated molecules

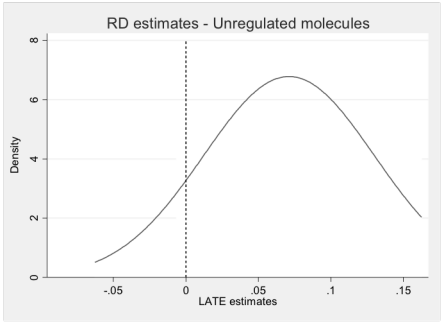


Notes: Vertical dotted lines (----) mark July 2013 (implementation of price regulation)

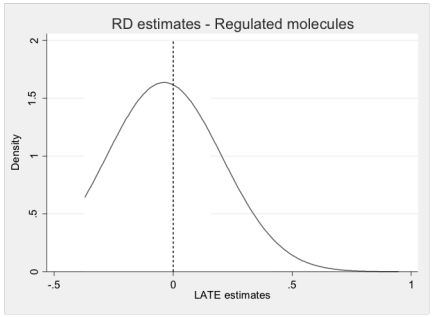
Figure 3 Distribution of treatment effects (LATE)

Outcome variable: log(sales units)

a. Unregulated molecules

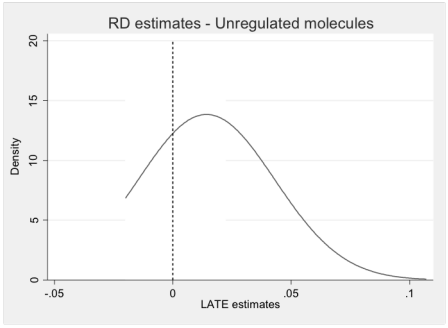


b. Regulated molecules



Outcome variable: log(RuralRx%)

c. Unregulated molecules



d. Regulated molecules

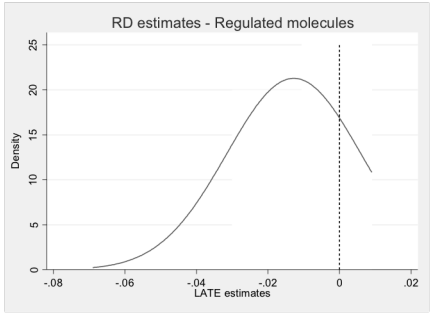
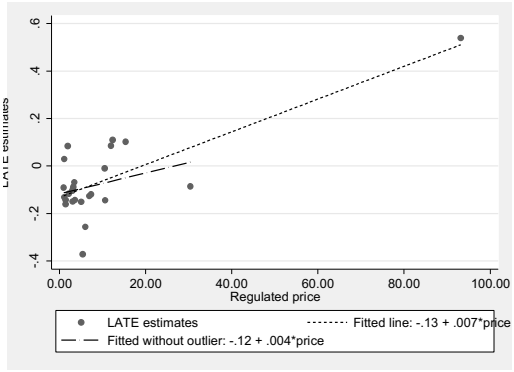


Figure 4 Regulated prices, percentage price reduction and LATE estimates

a. Regulated price and LATE



b. % price reduction and LATE

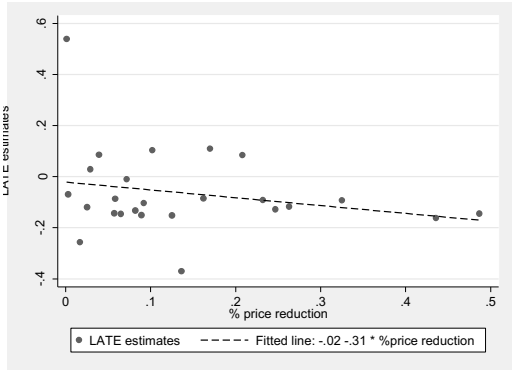


Figure 5 Detailing and sales volume: Brand UR and Brand R

a. Unregulated: Brand UR b. Regulated: Brand R

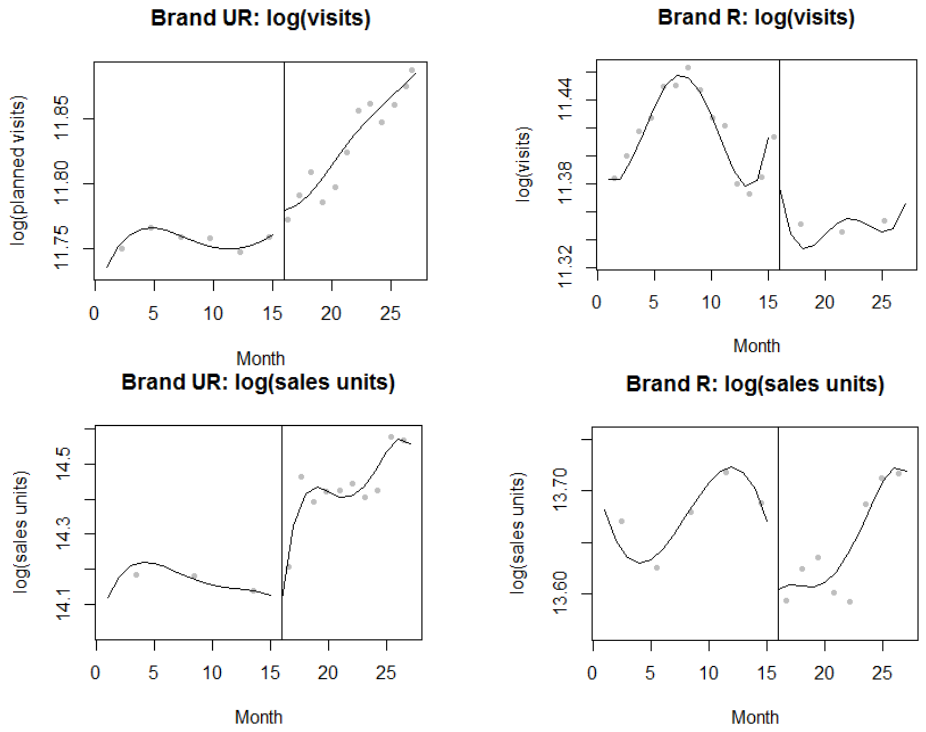


Table 1 Pre-regulation summary statistics

Sample Size[a]	*Unregulated Group: 57*		*Regulated Group: 51*		Difference[b,c]
Variable	Mean	SD	Mean	SD	
Sales (units)	34,828,103	79,750,198	27,742,658	29,659,619	-7,085,445
Log(sales)	16.404	1.454	16.401	1.447	-.003
C24R%	.332	.065	.354	.099	.022
RuralRx %	.043	.044	.072	.059	.029***
Type: Acute	.456	.503	.608	.493	.152
CPGPRx %	.455	.121	.417	.181	-.038

*** p<.01, ** p<.05, * p<.1

(a) No. of time periods per molecule: 50 months. Unregulated group has 2,850 and regulated group has 2,550 observations; (b) Difference = average regulated – average unregulated (in the pre-regulation period); (c) p-Value reported is for t-test (unregulated-regulated, two-tailed tests)

Table 2 Difference-in-difference estimates (post-regulation – pre-regulation)

	Unregulated Group: 57		*Regulated Group: 51*		Difference[b,c]
Variable[a]	Mean	SD	Mean	SD	
Δ Sales (units)	11,865,683	18,920,202	2,449,169	6,615,871	-9,416,514***
Δ Log(sales)	.617	.678	.084	.234	-.532***
Δ C24R%	.004	.010	.002	.008	-.002
Δ RuralRx %	.001	.014	-.003	.008	-.004*
Δ CPGPRx %	.003	.066	-.021	.031	-.024**

*** p<.01, ** p<.05, * p<.1

(a) Post-regulation values – Pre-regulation values for each molecule within the group (and then averaged); (b) Difference = average Δ regulated – average Δ unregulated (difference-in-difference); (c) p-Value reported is for t-test (regulated-unregulated, two-tailed tests)

Table 3 Panel fixed-effects regression: Average effect of regulation on outcomes

	Full sample			*Matched sample*		
Explanatory variables	(1)	(2)	(3)	(1)	(2)	(3)
PostReg	.053*	.034***	.086***	.287***	.051***	.085***
	(.029)	(.002)	(.016)	(.051)	(.003)	(.026)
IsNLEM * PostReg	-.090***	.000	-.273***	-.117***	-.012***	-.074***
	(.023)	(.001)	(.012)	(.044)	(.003)	(.022)
CPGPRx	.477	.217***	1.464***	.626	.182***	3.136***
	(.317)	(.017)	(.172)	(.467)	(.028)	(.231)
Constant	15.826***	-1.314***	-4.139***	15.760***	-1.240***	-4.611***
	(.141)	(.007)	(.076)	(.170)	(.010)	(.083)
Observations	6,555	6,646	6,584	1,738	1,798	1,748
R-squared	.852	.795	.730	.885	.845	.743
No. of molecules	108	108	108	29	29	29
Molecule FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Molecule*year FE	✓	✓	✓	✓	✓	✓

(1) Log (sales) (2) Log (C24R%) (3) Log (RuralRx%) Standard errors in parentheses

*** p<.01, ** p<.05, * p<.1

Table 4 Results of RD design, meta-analysis and SARIMA forecasts

	log(sales)		log(C24R%)		log(RuralRx%)	
	(1)	(2)	(1)	(2)	(1)	(2)
LATE estimate[a]	.071(24)	-.064(25)	.028(4)	-.011(7)	.033(16)	-.031(18)
Meta-Analysis[b]						
Effect size	.139***	-.354***	.129*	.051	.348**	-.142***
Fail-safe number	1,721	3,187	424	-	1,457	831
Meta-Analysis[c]						
Effect size	.303***	-.614***	1.393***	-.021	.779**	-.296***
Fail-safe number	1,705	2,861	304	-	1,361	633
SARIMA forecasts[d]						
ATE	.054	-.013	.116	-.006	.098	-.200

*** p<.01, ** p<.05, * p<.1

(1) Unregulated molecules (2) Regulated molecules

Parentheses – No. of molecules with significant LATE estimates

(a) Average LATE of molecules with significant LATE values

(b) Meta-analysis - all molecules (significant and insignificant LATE estimates)

(c) Meta-analysis – molecules with significant LATE

(d) Average $ATE_{actual\text{-}forecast}$ for molecules with significant LATE estimates

Table 5 RD estimates: Brand UR and Brand R

Outcome variable	*LATE estimates*	
	Brand UR	Brand R
log(visits)	.012*	-.056***
	(.007)	(.015)
log(new visits)	.161*	.139***
	(.100)	(.045)

log(non-core visits)	-.014	-.087***
	(.014)	(.016)
log(core visits)	.030***	-.037***
	(.012)	(.013)
log(sales volume)	.108***	-.069**
	(.002)	(.035)

Standard errors in parentheses
*** p<.01, ** p<.05, * p<.1

ONLINE APPENDICES

Online Appendix 1: List of molecules and descriptive measures

Table OA1.1 Regulated molecules

	Pre-regulation (mean)			*Post-regulation (mean)*		
Molecule	Sales (units)	C24R%	RuralRx%	Sales (units)	C24R%	RuralRx%
Acyclovir	1,769,909	35.5%	6.5%	2,290,356	35.4%	6.5%
Albendazole	4,751,608	48.6%	12.5%	5,140,623	48.8%	10.1%
Allopurinol	14,419,185	31.3%	3.8%	12,973,487	32.9%	3.8%
Alprazolam	53,972,281	37.5%	9.1%	50,964,214	39.0%	9.1%
Amiodarone	2,640,505	19.9%	1.4%	2,576,689	20.1%	.8%
Amlodipine	90,577,078	37.7%	7.5%	108,255,763	37.9%	6.0%
Amoxycillin/Clavulanate	26,177,973	39.3%	6.8%	43,411,322	39.1%	6.8%
Amoxycillin	34,429,063	47.8%	19.4%	33,407,763	48.9%	19.4%
Antithyroid preparations	6,827,610	37.9%	.7%	8,650,567	37.8%	.7%
Atenolol	43,897,092	44.0%	9.7%	39,910,427	42.8%	7.8%
Atorvastatin	56,860,179	29.0%	1.1%	59,988,171	29.0%	1.1%
Azathioprine	2,287,797	14.2%	2.6%	2,598,225	14.8%	2.4%
Azithromycin	13,103,179	42.2%	10.8%	14,563,998	43.2%	10.9%
Bisacodyl	22,576,401	40.8%	7.7%	24,960,924	38.6%	7.7%
Cardiac glycosides	15,048,620	43.8%	4.9%	16,401,441	43.8%	3.9%
Cefixime	54,839,233	51.7%	18.5%	61,300,037	51.8%	18.5%
Cephalexin	6,099,180	46.2%	15.4%	6,066,248	46.5%	15.4%
Cetirizine	74,270,127	48.0%	20.5%	83,205,504	49.0%	22.6%
Clindamycin	1,172,628	25.7%	3.2%	1,807,759	24.8%	3.2%
Clopidogrel	32,212,158	26.9%	2.2%	34,525,103	28.7%	1.2%
Diclofenac	30,239,580	43.4%	14.2%	24,876,323	43.9%	14.2%
Domperidone	13,968,566	31.2%	10.8%	12,949,214	31.6%	10.8%
Enalapril	16,694,349	42.7%	4.7%	15,042,128	42.9%	2.1%
Fluconazole	6,824,991	40.9%	10.8%	8,208,995	41.6%	10.8%
Glibenclamide	31,441,286	38.4%	7.0%	24,522,674	37.0%	7.0%
Hydroxychloroquine	8,016,134	25.1%	.7%	11,062,944	26.2%	.7%
Hyoscine	7,313,119	44.3%	7.7%	7,874,736	43.8%	7.7%
Imatinib	209,690	4.9%	7.0%	193,482	4.2%	4.7%
Isosorbide-5-mononitrate	9,935,075	30.0%	3.4%	10,061,415	30.4%	3.4%
Leflunomide	926,471	18.4%	1.0%	1,194,522	18.5%	.7%
Levothyroxine	104,844,435	26.8%	.8%	125,581,644	26.9%	.8%
Losartan	32,889,273	35.4%	3.5%	34,373,522	34.6%	3.8%
Medroxyprogesterone	4,734,642	33.4%	2.0%	5,307,746	34.8%	2.0%
Metformin	95,253,160	28.4%	3.2%	124,174,334	28.3%	3.2%
Methylergometrine	4,304,485	48.0%	19.0%	4,277,639	47.9%	19.1%
Metoprolol	30,515,111	29.6%	2.5%	40,065,700	29.9%	2.5%

Mifepriston	525,343	47.3%	5.3%	171,195	46.8%	5.3%
Nifedipine	16,084,923	38.6%	3.6%	16,521,116	38.7%	3.6%
Nitrofurantoin	4,103,859	25.7%	.9%	6,033,057	26.8%	.9%
Norethisterone	20,750,889	39.6%	4.6%	22,706,459	39.4%	5.1%
Ofloxacin	45,809,352	46.6%	21.4%	36,601,520	46.7%	21.4%
Olanzepine	6,307,254	27.1%	1.9%	6,834,783	27.4%	.9%
Omeprazole	57,082,163	43.7%	18.5%	64,544,938	43.5%	18.7%
Ondansetron	15,520,939	38.5%	11.0%	20,507,187	38.0%	11.0%
Others - Folic acid	48,396,839	30.4%	4.9%	54,127,731	31.8%	4.9%
Paracetamol	122,169,033	48.7%	13.3%	118,383,877	48.6%	13.2%
Phenytoin	71,683,918	32.9%	3.2%	72,437,839	33.9%	3.2%
Propranolol	12,230,254	32.6%	3.2%	14,405,796	32.9%	2.1%
Pyrazinamide	2,928,813	21.6%	4.9%	3,066,078	20.6%	3.8%
Sodium valproate	17,532,340	29.8%	3.9%	17,678,465	29.6%	3.9%
Trihexyphenidyl	17,707,489	31.8%	2.3%	22,997,495	31.5%	1.7%

Table OA1.2 Unregulated molecules

	Pre-regulation (mean)			*Post-regulation (mean)*		
Molecule	Sales (units)	C24R%	RuralRx%	Sales (units)	C24R%	RuralRx%
Dpp4 inhibitors and combinations	19,772,240	17.7%	.2%	50,143,040	20.3%	.3%
Glimepiride/Metformin	118,641,469	31.6%	1.0%	212,828,020	31.7%	.9%
Pantoprazole/Domperidone	48,636,418	37.0%	8.7%	72,515,953	37.5%	8.7%
Rosuvastatin	22,991,779	26.5%	1.4%	45,570,295	26.6%	1.5%
Rabeprazole/Domperidone	52,612,334	39.2%	6.5%	73,637,944	39.1%	8.0%
Ranitidine	594,391,374	48.0%	17.6%	703,449,821	48.5%	18.0%
Pantoprazole	60,544,714	33.5%	9.0%	80,692,616	33.1%	8.8%
Levocetirizine/Montelukast	27,581,583	38.2%	5.1%	49,961,074	38.4%	5.2%
Pioglitazone/Metformin/Glimepiride	51,827,764	36.0%	1.7%	54,135,370	36.3%	2.0%
Cefpodoxime	36,050,565	46.5%	13.4%	47,472,936	47.3%	14.6%
Telmisartan/ Hydrochlorothiazide	31,099,636	30.9%	1.2%	48,089,339	33.5%	1.4%
Atenolol/Amlodipine	124,913,756	41.1%	9.3%	144,168,107	41.7%	10.6%
Cefuroxime	12,112,256	31.6%	7.4%	13,856,915	32.1%	7.7%
Levetiracetam	11,151,615	25.0%	2.5%	22,742,361	24.9%	4.9%
Omeprazole/Domperidone	67,683,259	46.8%	18.3%	90,364,399	46.9%	17.8%
Glimepiride/Metformin/Voglibose	2,600,749	30.3%	.0%	16,361,777	31.0%	.1%
Amlodipine/Telmisartan	17,050,277	32.6%	1.0%	33,207,261	32.2%	1.6%
Ursodeoxycholic acid	11,675,020	28.4%	1.7%	15,170,618	28.7%	1.8%
Rabeprazole	56,954,048	36.5%	6.3%	59,691,992	35.9%	6.7%
Gliclazide/Metformin	37,145,096	34.0%	3.1%	41,791,892	34.0%	3.7%
Sildenafil	10,149,794	36.9%	4.5%	10,221,839	36.2%	4.3%
Voglibose	23,120,165	29.4%	.7%	37,790,723	32.7%	.9%

Ofloxacin/Ornidazole	31,186,736	43.4%	9.4%	35,425,920	43.8%	9.3%
Cefpodoxime/Clavulanate	8,398,350	40.2%	6.0%	11,991,900	40.3%	6.3%
Aceclofenac/Paracetamol	63,991,413	43.9%	10.5%	78,111,885	44.3%	1.0%
Losartan/Hydrochlorthiazide	42,321,096	38.9%	1.8%	44,200,042	38.8%	1.5%
Olmesartan	13,580,719	28.5%	.8%	23,366,815	32.9%	.6%
Ramipril	34,848,608	26.5%	3.0%	34,444,862	26.6%	2.9%
Levosulpiride/Rabeprazole	4,342,038	34.0%	2.6%	12,385,175	34.4%	3.9%
Itraconazole	461,776	26.9%	3.2%	2,158,354	26.1%	3.7%
Cilnidipine	2,975,158	36.4%	.6%	16,600,465	35.3%	.4%
Dutasteride/Tamsulosin	6,788,841	31.8%	.7%	10,433,490	31.0%	.5%
Esomeprazole/Domperidone	10,026,629	33.7%	3.6%	17,505,073	34.8%	4.1%
Rosuvastatin/Fenofibrate	3,951,021	23.2%	.4%	9,607,510	24.4%	.6%
Levocetirizine	44,547,018	38.8%	7.9%	51,662,773	39.3%	8.2%
Levofloxacin	26,670,562	38.7%	11.3%	23,609,808	38.4%	10.6%
Amlodipine/Metoprolol	14,257,340	33.0%	1.5%	22,130,955	32.8%	1.6%
Chlortalidone/Telmisartan	2,032,771	24.3%	.4%	8,295,876	24.6%	.7%
Etorecoxib	14,841,524	37.3%	4.8%	16,670,605	37.9%	4.9%
Hydrochlorthiazide/Olmesartan	9,709,078	29.9%	.5%	14,756,272	31.0%	.3%
Esomeprazole	16,746,021	28.6%	2.4%	23,517,340	29.6%	2.9%
Terbinafine	3,298,504	35.5%	8.8%	6,317,371	35.8%	9.6%
Fenofibrate/Atorvastatin	11,496,910	26.3%	.5%	13,012,433	27.2%	.6%
Metformin/Voglibose	5,775,630	30.3%	.6%	15,489,492	30.5%	.6%
Rifaximin	2,211,774	25.6%	1.5%	4,651,646	25.6%	1.3%
Fexofenadine	8,464,660	21.9%	2.4%	9,864,678	21.7%	3.0%
Montelukast/Fexofenadine	2,581,820	33.6%	2.3%	7,192,374	32.8%	2.9%
Tamsulosin	10,851,297	31.4%	1.4%	14,602,923	30.9%	1.2%
Gliclazide	17,191,328	26.5%	2.7%	18,937,863	26.5%	2.2%
Levosulpiride/Pantoprazole	1,945,930	29.8%	3.0%	5,514,453	29.8%	3.2%
Cefixime/Ofloxacin	18,357,920	39.7%	14.3%	31,799,134	39.0%	15.1%
Colecalciferol	4,904,851	23.8%	5.0%	16,399,733	24.6%	4.4%
Atorvastatin/Aspirin	32,746,182	33.6%	1.1%	51,926,328	34.6%	1.6%
Nebivolol	14,035,872	29.8%	.5%	17,542,361	29.6%	.7%
Clavulanic acid/Cefuroxime	2,267,808	35.7%	1.5%	2,885,516	36.1%	1.4%
Glibenclamide/Metformin	41,502,233	40.5%	2.6%	42,809,110	40.9%	4.3%
Torsemide	17,186,564	30.9%	2.1%	21,860,985	30.9%	2.2%

Online Appendix 2: Results of panel fixed-effects regression models

Table OA2.1 Panel regression results

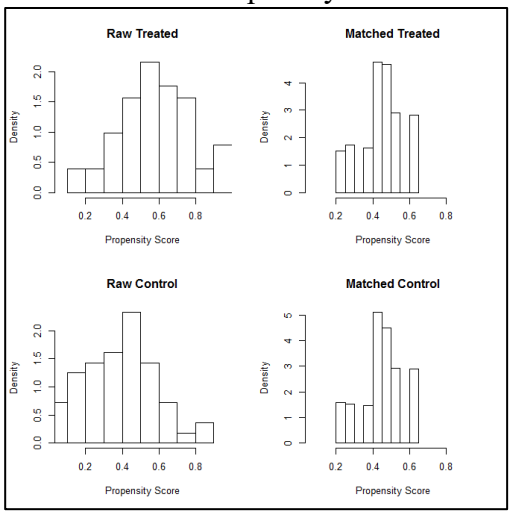
	log(sales)			*log(C24R%)*				*log(RuralRx%)*			
Explanatory variables	(1)	(2)	(3)[a]	(1)	(2)	(3)[a]	(4)[b]	(1)	(2)	(3)[a]	(4)[b]
PostReg	.305***	.053*	.056***	.034***	.034***	.033***	.049***	.107***	.086***	.079***	.084***
	(.058)	(.029)	(.020)	(.003)	(.002)	(.002)	(.002)	(.026)	(0.016)	(.016)	(.017)
IsNLEM * PostReg	-.483***	-.090***	-.090***	.000	.000	.000	.002	-.384***	-.273***	-.273***	-.288***
	(.027)	(.023)	(.023)	(.001)	(.001)	(.001)	(.002)	(.014)	(.012)	(.012)	(.013)
CPGPRx%	1.831***	.477	.477	.226***	.217***	.219***	.346***	1.785***	1.464***	1.464***	1.839***
	(.380)	(.317)	(.317)	(.016)	(.017)	(.017)	(.024)	(.165)	(.172)	(.172)	(.176)
Constant	15.288***	15.826***	15.818***	-1.207***	-1.314***	-1.306***	-.831***	-4.128***	-4.139***	-4.132***	-4.092***
	(.172)	(.141)	(.141)	(.007)	(.007)	(.007)	(.011)	(.074)	(.076)	(.076)	(.078)
Observations	6,555	6,555	6,555	6,646	6,646	6,646	6,646	6,584	6,584	6,584	6,584
R-squared	.269	.852	.852	.337	.795	.795	.807	.129	.730	.730	.732
No. of Molecules	108	108	108	108	108	108	108	108	108	108	108
Molecule FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Molecule-year FE		✓	✓		✓	✓	✓		✓	✓	✓
Polynomial Time trend			✓			✓	✓			✓	✓

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

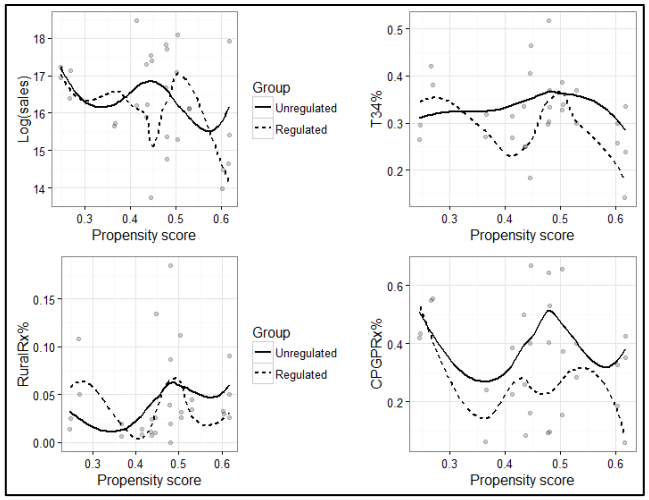
(a) Time trend added as a robustness check (polynomial time trend – t, t^2 and t^3 added to the panel regression)
(b) Logit transformation of dependent variables - log (y%/(1-y%)) – y →(C24R% and RuralRx%)

Online Appendix 3: Balance of covariates after matching

a. Propensity scores



b. Covariate distributions



Online Appendix 4: RDD results

Table OA4.1 RD results: Regulated molecules

	log(sales units)			*log(C24R%)*			*log(RuralRx%)*		
Molecule	LATE[a]	Effect size[b]	ATE[c]	LATE[a]	Effect size[b]	ATE[c]	LATE[a]	Effect size[b]	ATE[c]
Acyclovir	**.110**	**.410**	**.377**	-.002	-.247	-.015	-.005	-.023	-.002
Albendazole	-.057	-.445	-.054	.007	.981	.028	**-.044**	**-.399**	**-.211**
Allopurinol	-.080	-.495	**-.240**	**.034**	**1.606**	**.049**	-.004	-.055	-.008
Alprazolam	-.036	-.515	-.015	**.016**	**1.595**	**.037**	-.009	-.076	-.005
Amiodarone	**-.127**	**-.549**	**-.026**	.006	.973	.027	**-.052**	**-.277**	**-.489**
Amlodipine	**-.104**	**-.749**	**-.018**	-.007	-.868	-.005	**-.069**	**-.864**	**-.129**
Amoxycillin	.133	.248	.021	.004	.614	.005	-.015	-.029	-.001
Amoxycillin/Clavulanate	.088	.497	.012	.004	.568	.024	-.002	-.013	-.001
Antithyroid preparations	.003	.016	-.017	.005	.623	.015	.001	.023	.003
Atenolol	**-.117**	**-1.757**	**-.064**	**-.013**	**-1.730**	**-.030**	**-.043**	**-.371**	**-.107**
Atorvastatin	-.041	-.453	-.015	-.001	-.070	-.021	-.005	-.172	-.003
Azathioprine	**-.010**	**-.206**	**-.025**	.036	.629	.024	**-.024**	**-.316**	**-.047**

Azithromycin	.089	.509	-.024	.021	.544	**.017**	-.022	-.116	**-.018**
Bisacodyl	.068	.368	.054	**-.052**	**-2.999**	**-.085**	.005	.142	.007
Cardiac glycosides	-.087	-.462	-.025	.001	.667	.025	**-.064**	**-.450**	**-.189**
Cefixime	**.086**	**.323**	**.023**	-.002	-.696	-.024	-.005	-.259	-.007
Cephalexin	.014	.089	.025	-.003	-.498	-.031	-.004	-.203	-.006
Cetirizine	**.084**	**.593**	**.096**	-.004	-.530	-.026	**.036**	**.326**	**.049**
Clindamycin	.083	.163	.125	-.012	-.094	.020	.018	.033	.019
Clopidogrel	**-.145**	**-1.192**	**-.036**	**.037**	**.836**	**.059**	**-.087**	**-.881**	**-.164**
Diclofenac	-.115	-1.181	.057	.014	.314	.026	-.056	-.230	.016
Domperidone	-.031	-.250	.245	.007	.416	.021	-.088	-.477	**-.048**
Enalapril	-.145	-1.469	.185	.009	.133	.036	**-.075**	**-.692**	**-.407**
Fluconazole	**.103**	**.537**	**.161**	.009	.273	-.045	-.008	-.215	.004
Glibenclamide	**-.091**	**-.535**	**-.035**	-.005	-.611	-.039	.003	.330	.005
Hydroxychloroquine	**-.257**	**-.987**	**-.011**	.004	.334	-.026	.002	.105	.004
Hyoscine	.103	.547	.200	-.002	-.315	.035	.004	.106	.007
Imatinib	**.539**	**.712**	**.102**	**-.109**	**-1.550**	**-.102**	**-.056**	**-.464**	**-.414**
Isosorbide-5-mononitrate	**-.069**	**-.862**	**.018**	-.001	-.070	.017	-.003	-.215	-.008
Leflunomide	**-.086**	**-.717**	**-.130**	.002	.115	.018	**-.048**	**-.513**	**-.371**
Levothyroxine	**-.132**	**-.804**	**-.075**	.017	.325	.029	-.002	-.221	-.008
Losartan	-.146	-1.692	.048	.010	.179	.075	**.032**	**.398**	**.070**
Medroxyprogesterone	-.134	-1.045	**-.115**	.012	.285	.016	.009	.502	.008
Metformin	-.030	-.173	**-.066**	-.006	-.524	.079	-.010	-.179	-.002
Methylergometrine	.011	.106	.075	-.004	-.364	-.055	-.013	-.295	**-.041**
Metoprolol	**-.143**	**-.639**	**-.063**	.006	.399	-.039	.002	.239	.004
Mifepriston	-.059	-.126	-.120	-.002	-.256	-.004	-.004	-.127	-.005
Nifedipine	-.023	-.315	**-.243**	.016	.632	.014	-.005	-.205	-.008
Nitrofurantoin	-.006	-.018	-.032	.029	.351	-.024	-.005	-.116	-.007
Norethisterone	**-.371**	**-3.418**	**-.055**	-.006	-.179	.004	**.039**	**.221**	**.278**
Ofloxacin	.177	.858	.015	-.009	-.283	**-.085**	-.004	-.151	-.003
Olanzepine	**-.150**	**-1.326**	**-.104**	.004	.332	.024	**-.023**	**-.419**	**-.468**
Omeprazole	**-.093**	**-1.024**	**-.136**	.004	.523	.011	**.023**	**.338**	**.029**
Ondansetron	**-.151**	**-.839**	**-.024**	-.014	-.277	-.107	.004	.161	.002
Others - Folic acid	**-.144**	**-.550**	**-.085**	.006	.317	-.008	.005	.115	.007
Paracetamol	.143	.747	.157	-.011	-.353	**-.116**	-.010	.147	**.005**
Phenytoin	.289	1.860	.041	**.011**	**.425**	**.032**	.007	.211	.001
Propranolol	**.029**	**.307**	**.029**	-.001	-.054	-.004	**-.042**	**-.319**	**-.370**

Pyrazinamide	**-.119**	**-.624**	**-.033**	.007	.536	.005	**-.023**	**-.305**	**-.305**
Sodium valproate	**-.087**	**-1.051**	**-.124**	.020	.107	.104	.009	.153	.006
Trihexyphenidyl	**-.162**	**-.814**	**-.090**	-.027	-.375	**-.057**	**-.042**	**-.439**	**-.350**

Notes: Boldface indicates statistical significance (p<.05)
(a) RD coefficients (b) Standard mean change (effect size) (c) Difference between actual outcomes and forecast values

Table OA4.2 RD results: Unregulated molecules

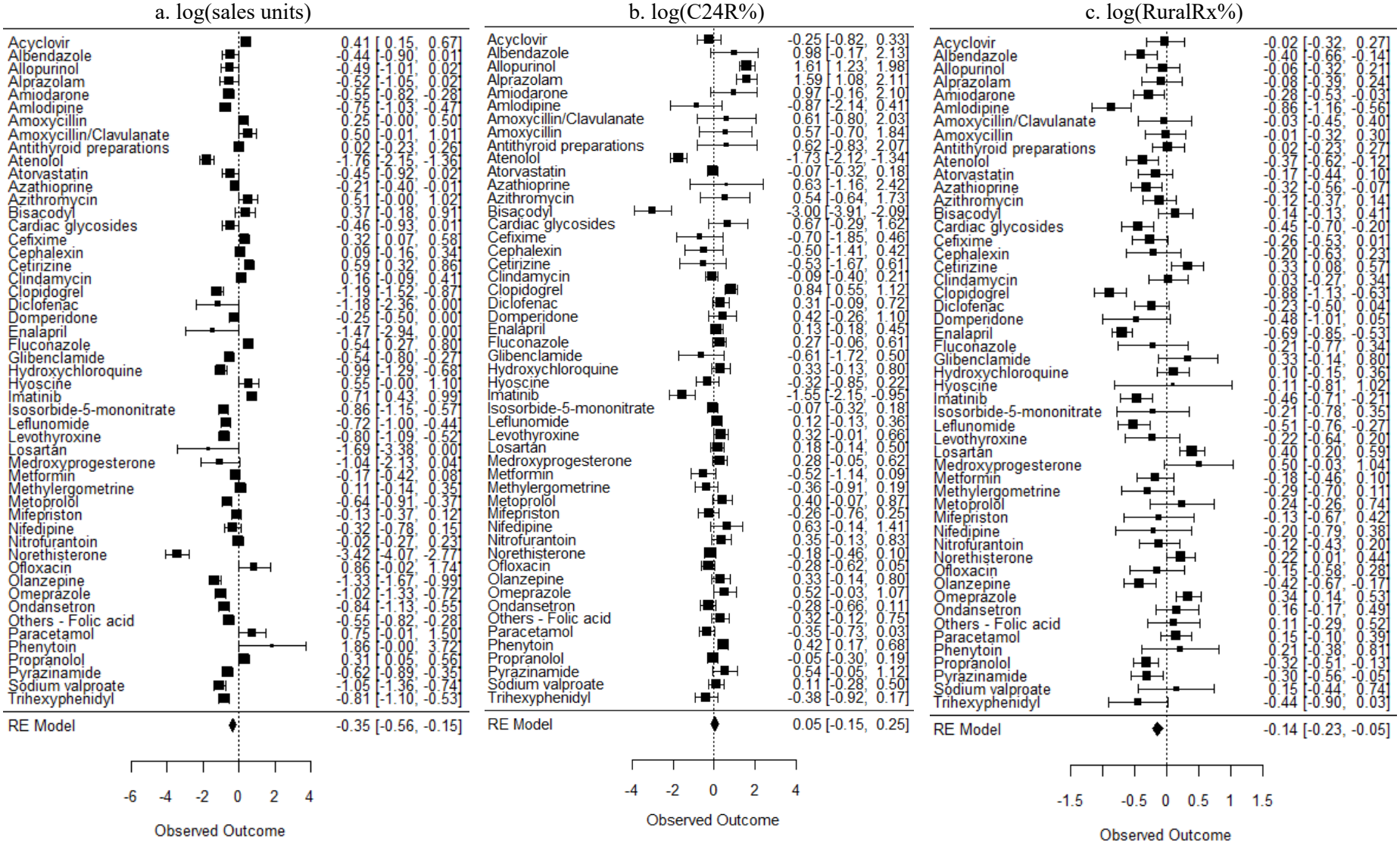
	log(sales units)			*log(C24R%)*			*log(RuralRx%)*		
Molecule	LATE[a]	Effect size[b]	ATE[c]	LATE[a]	Effect size[b]	ATE[c]	LATE[a]	Effect size[b]	ATE[c]
Dpp4 inhibitors and combinations	**.035**	**.054**	**-.022**	**.026**	**1.375**	**.137**	.021	.272	.004
Glimepiride/Metformin	**.030**	**.114**	**.067**	-.017	-.510	.021	.005	.140	-.003
Pantoprazole/Domperidone	**.061**	**.267**	**.024**	.016	.583	.025	.002	.518	-.006
Rosuvastatin	.005	.009	**.015**	.022	.438	-.024	-.010	-1.024	-.008
Rabeprazole/Domperidone	**.074**	**.376**	**.031**	-.006	-.418	-.026	**.067**	**1.523**	**.212**
Ranitidine	**.162**	**1.077**	**.111**	.002	.271	.019	**.054**	**1.499**	**.081**
Pantoprazole	**.037**	**.211**	**-.010**	.003	.278	.004	-.012	-.106	-.008
Levocetirizine/Montelukast	.086	.187	-.121	-.003	-.361	.002	.006	.121	.004
Pioglitazone/Metformin/Glimepiride	-.051	-.539	.009	.006	.480	-.013	.029	.130	.015
Cefpodoxime	.185	.714	-.061	.011	.335	-.017	**.025**	**.438**	**.040**
Telmisartan/ Hydrochlorothiazide	**.032**	**.107**	**.013**	**.026**	**2.558**	**.081**	.063	.328	.012
Atenolol/Amlodipine	**.020**	**.200**	**.018**	.021	.606	-.021	**.103**	**2.221**	**.137**
Cefuroxime	.068	.549	.112	.001	.092	.005	.043	.391	-.006
Levetiracetam	**.050**	**.112**	**.014**	-.007	-.382	-.011	**.025**	**2.075**	**.700**
Omeprazole/Domperidone	**-.016**	**-.079**	**.019**	.002	.217	.010	-.012	-.330	-.033
Glimepiride/Metformin/Voglibose	.071	.047	.109	.013	.208	.021	.003	.027	.001
Amlodipine/Telmisartan	**.038**	**.082**	**.006**	.004	.452	.010	.022	.416	**.015**
Ursodeoxycholic acid	.028	.139	-.008	.003	.265	.003	.021	.293	-.004
Rabeprazole	.022	.282	.033	.010	.132	-.003	.009	1.084	.002
Gliclazide/Metformin	-.002	-.028	.068	.009	.198	-.018	**.093**	**1.300**	**.103**
Sildenafil	-.013	-.131	.152	-.001	-.091	.010	.019	.541	-.003
Voglibose	.023	.082	-.062	**.013**	**1.142**	**.105**	.065	.592	**.102**
Ofloxacin/Ornidazole	-.083	-.441	.126	-.007	-.036	-.025	-.003	-.393	.001
Cefpodoxime/Clavulanate	**.129**	**.378**	**.152**	-.008	-.332	-.024	.065	.455	.038
Aceclofenac/Paracetamol	**.148**	**.969**	**.042**	-.007	-.227	-.013	**-.202**	**-1.134**	**-0.734**
Losartan/Hydrochlorthiazide	-.026	-.439	-.009	-.013	-.493	.002	-.048	-.541	-.049
Olmesartan	.017	.047	.143	**.045**	**.576**	**.141**	-.044	-.012	.061

Ramipril	**-.063**	**-1.293**	**.040**	.004	.052	-.007	-.019	-.575	-.028
Levosulpiride/Rabeprazole	**.088**	**.081**	**.135**	.008	.669	-.024	**.107**	**1.328**	**-.412**
Itraconazole	.098	.043	-.025	.014	.147	-.017	.036	.637	.046
Cilnidipine	-.069	-.085	**.177**	-.019	-1.006	**-.058**	**-.073**	**-1.153**	**-.288**
Dutasteride/Tamsulosin	**.108**	**.443**	**.063**	.001	.063	.038	.034	.877	.057
Esomeprazole/Domperidone	**.091**	**.321**	**.031**	.015	.591	.043	**.043**	**.327**	**.252**
Rosuvastatin/Fenofibrate	**.053**	**.058**	**.097**	.040	.720	**.051**	**.021**	**.683**	**-.083**
Levocetirizine	**.140**	**1.162**	**.054**	-.018	-.192	.000	.015	.499	.026
Levofloxacin	.103	.760	-.046	-.010	-.270	-.031	-.016	-.292	-.025
Amlodipine/Metoprolol	-.002	-.006	.132	-.002	-.162	.050	-.008	-.189	.030
Chlortalidone/Telmisartan	-.115	-.146	**-.201**	-.011	-.533	-.016	.020	.145	.002
Etorecoxib	-.034	-.447	-.015	-.003	-.379	.005	-.062	-.406	.015
Hydrochlorthiazide/Olmesartan	.003	.009	-.098	.029	.820	**.050**	-.138	-.257	-.058
Esomeprazole	**.104**	**.687**	**.047**	.022	.176	-.027	**.027**	**.331**	**.329**
Terbinafine	**.157**	**.456**	**.190**	-.011	-1.063	.022	**.018**	**.296**	**.109**
Fenofibrate/Atorvastatin	-.053	-.487	-.067	.021	.630	-.043	.007	.234	-.005
Metformin/Voglibose	.017	.015	.073	-.006	-.108	.017	-.003	-.194	.004
Rifaximin	-.070	-.149	-.073	.019	.020	-.015	-.028	-.503	-.080
Fexofenadine	**.161**	**.941**	**.119**	-.014	-.609	-.002	**.062**	**.829**	**.343**
Montelukast/Fexofenadine	.054	.062	.027	.012	.243	-.047	.041	.355	-.044
Tamsulosin	**.043**	**.275**	**.025**	-.004	-.311	.004	-.065	-.012	.006
Gliclazide	.013	.286	.073	.003	.257	.036	-.076	-.306	-.065
Levosulpiride/Pantoprazole	-.056	-.076	-.014	.003	.277	-.049	.078	.151	-.004
Cefixime/Ofloxacin	.105	.116	-.024	-.005	-.586	-.004	.017	.376	.027
Colecalciferol	-.035	-.040	-.025	-.015	-.078	.015	-.026	-.414	-.009
Atorvastatin/Aspirin	.019	.056	-.053	.029	.028	-.008	**.043**	**.742**	**.265**
Nebivolol	-.030	-.221	-.044	-.011	-.117	-.031	.033	.157	.037
Clavulanic acid/Cefuroxime	.069	.369	-.028	.031	.500	.023	.025	.106	-.006
Glibenclamide/Metformin	**.025**	**.444**	**.032**	-.012	-.462	-.017	**.108**	**1.309**	**.521**
Torsemide	.003	.020	.023	-.003	-.071	.002	.033	.460	.037

Notes: Boldface indicates statistical significance ($p<.05$)

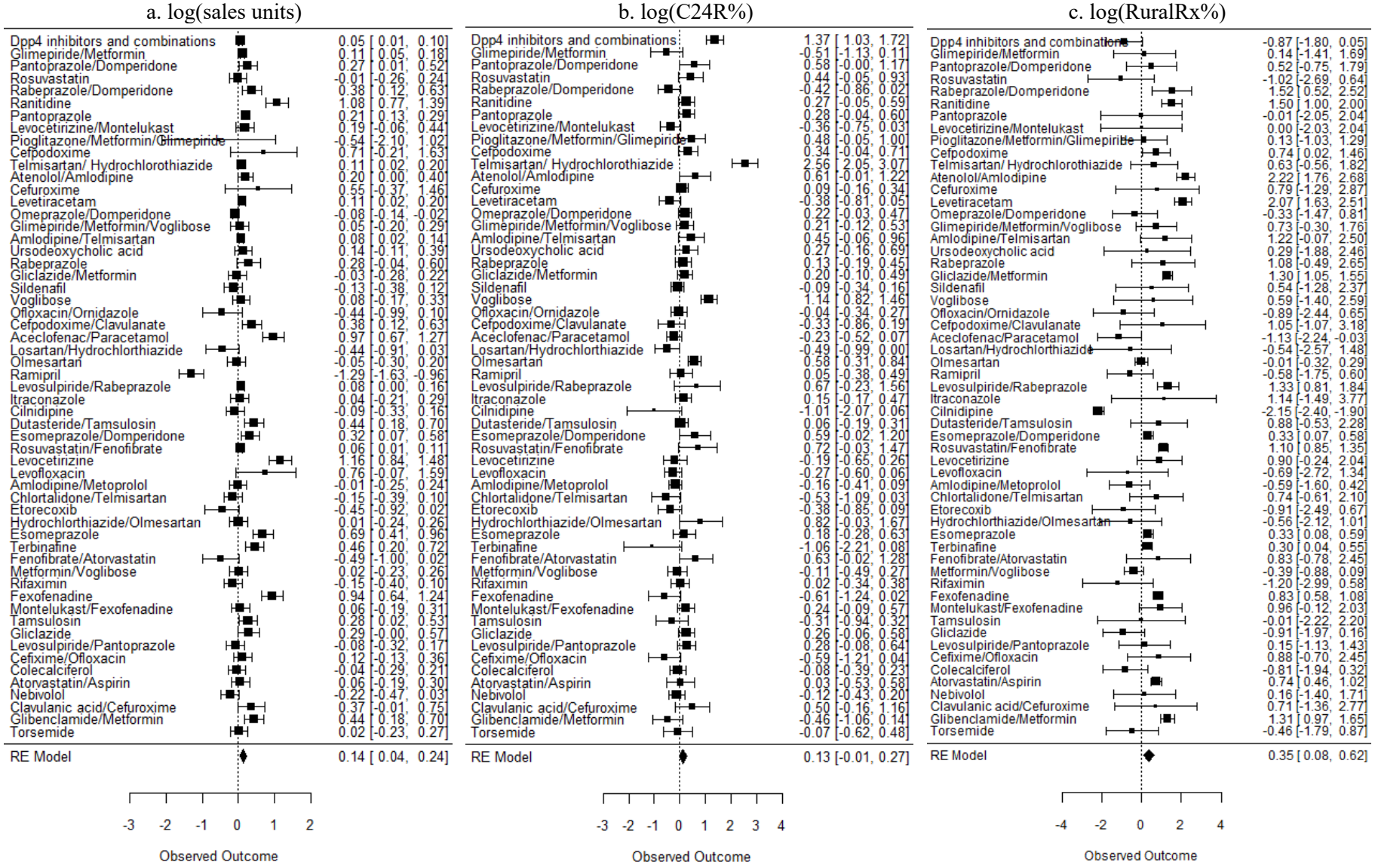
(a) RD coefficients (b) Standard mean change (effect size) (c) Difference between actual outcomes and forecast values

Figure OA 4.1 Meta-analysis illustration: Regulated molecules (with 95% Confidence Intervals)



* RE refers to random-effects model in computing the weighted effect size

Figure OA 4.2 Meta-Analysis illustration: Unregulated molecules (with 95% Confidence Intervals)



* RE refers to random-effects model in computing the weighted effect size

Online Appendix 5: Placebo tests (RD design)

Notes: Placebo 1: RD coefficient in the pre-regulation period (20 months: December 2010)
Placebo 2: RD coefficient in the pre-regulation period (30 months: October 2011 – NLEM list announced)
Placebo 3: RD coefficient in the pre-regulation period (35 months: March 2012)
Placebo 4: RD coefficient in the post-regulation period (6 months: December 2013)
Boldface indicates statistical significance (p<.05)

Table OA5.1 Regulated molecules: log(sales)

	Placebo 1		*Placebo 2*		*Placebo 3*		*Placebo 4*	
Molecule	LATE	p-Value	LATE	p-Value	LATE	p-Value	LATE	p-Value
Acyclovir	.347	**.020**	.024	.876	.021	.903	.049	.640
Amiodarone	-.082	.563	-.007	.961	.040	.804	-.093	.481
Amlodipine	.061	.303	.014	.811	.027	.678	-.056	.509
Atenolol	.025	.473	.021	.548	.078	**.036**	-.091	.357
Azathioprine	.077	.268	.022	.764	.038	.630	.027	.658
Cefixime	-.105	.452	-.180	.202	-.013	.936	-.220	**.022**
Cetirizine	-.054	.511	-.057	.488	-.055	.551	-.149	.160
Clopidogrel	.087	.122	-.016	.767	-.017	.783	-.066	.417
Fluconazole	.029	.797	-.081	.472	.033	.792	-.165	.106
Glibenclamide	.003	.965	.039	.624	-.064	.458	-.116	.288
Hydroxychloroquine	.048	.683	.018	.885	.051	.700	-.094	.357
Imatinib	-.212	.658	.747	.123	-.102	.848	-.165	.535
Isosorbide-5-mononitrate	.050	.242	.003	.940	.033	.498	-.055	.552
Leflunomide	.178	.369	-.050	.806	-.095	.667	-.022	.743
Levothyroxine	.059	.449	.010	.898	.058	.506	.011	.942
Metoprolol	.112	.232	-.049	.611	-.040	.702	-.041	.607
Norethisterone	.013	.757	-.042	.338	-.035	.466	-.187	.309
Olanzepine	.051	.333	-.009	.860	-.008	.892	-.096	.242
Omeprazole	.050	.254	.046	.274	.054	.225	-.039	.646
Ondansetron	-.059	.419	-.072	.335	.155	.053	-.109	.267
Others - Folic acid	.075	.636	-.189	.245	-.038	.831	.152	.211
Propranolol	.081	.316	-.037	.651	.083	.354	-.069	.466
Pyrazinamide	.037	.731	-.031	.770	.087	.457	-.160	.287
Sodium valproate	.029	.489	.048	.226	.036	.397	-.034	.624
Trihexyphenidyl	.002	.988	-.087	.393	-.057	.608	-.161	.392

Table OA5.2 Unregulated molecules: log(sales)

	Placebo 1		*Placebo 2*		*Placebo 3*		*Placebo 4*	
Molecule	LATE	p-Value	LATE	p-Value	LATE	p-Value	LATE	p-Value
Dpp4 inhibitors and combinations	.067	.072	.002	.950	-.016	.700	.001	.986
Glimepiride/Metformin	.050	.074	-.048	.080	-.019	.548	-.039	.605
Pantoprazole/Domperidone	.004	.926	-.036	.374	.046	.304	-.073	.220

Rabeprazole/Domperidone	.037	.382	-.036	.385	.063	.159	-.063	.376
Ranitidine	.042	.402	-.054	.287	.043	.442	-.063	.549
Pantoprazole	.020	.558	-.031	.336	.020	.589	-.034	.561
Telmisartan/ Hydrochlorothiazide	.104	**.001**	.011	.681	-.003	.923	-.006	.932
Atenolol/Amlodipine	.022	.415	-.007	.810	-.014	.635	.015	.824
Levetiracetam	.061	**.017**	-.011	.639	-.027	.333	-.028	.713
Omeprazole/Domperidone	-.004	.943	.073	.255	.198	**.003**	-.109	.157
Amlodipine/Telmisartan	.103	**.002**	-.032	.357	-.095	**.024**	.011	.872
Cefpodoxime/Clavulanate	-.042	.613	-.059	.468	-.032	.730	-.070	.203
Aceclofenac/Paracetamol	.001	.979	-.058	.227	.054	.311	-.085	.491
Ramipril	.039	.127	-.009	.734	-.016	.563	-.017	.807
Levosulpiride/Rabeprazole	.048	.257	.027	.784	.004	.825	.002	.687
Dutasteride/Tamsulosin	.014	.628	-.068	**.018**	-.058	.088	-.047	.520
Esomeprazole/Domperidone	.000	.995	.094	.035	.163	**.000**	-.068	.305
Rosuvastatin/Fenofibrate	.430	**.000**	-.154	**.041**	-.276	**.015**	-.039	.608
Levocetirizine	-.068	.293	-.052	.426	-.032	.661	-.120	**.042**
Esomeprazole	.001	.972	.018	.574	.068	**.041**	-.062	.337
Terbinafine	-.112	.230	-.141	.131	.066	.534	-.159	.104
Fexofenadine	-.003	.967	-.021	.724	-.069	.310	-.170	**.006**
Tamsulosin	.030	.302	-.017	.553	.023	.463	-.047	.567
Glibenclamide/Metformin	.081	**.009**	.026	.408	.019	.576	-.010	.894

Table OA5.3 Regulated molecules: log(C24R%)

	Placebo 1		*Placebo 2*		*Placebo 3*		*Placebo 4*	
Molecule	LATE	p-Value	LATE	p-Value	LATE	p-Value	LATE	p-Value
Allopurinol	-.007	.194	.005	.389	-.003	.592	.014	.281
Alprazolam	.007	.154	.005	.347	.004	.408	-.014	**.011**
Atenolol	-.004	.370	-.007	.125	-.007	.170	-.017	.156
Bisacodyl	.002	.724	.003	.461	.001	.815	.017	.162
Clopidogrel	-.003	.614	.002	.751	.002	.814	-.011	.544
Imatinib	-.001	.827	.012	.674	.005	.832	.009	.679
Phenytoin	-.012	**.013**	-.002	.700	-.008	.139	-.011	.419

Table OA5.4 Unregulated molecules: log(C24R%)

	Placebo 1		*Placebo 2*		*Placebo 3*		*Placebo 4*	
Molecule	LATE	p-Value	LATE	p-Value	LATE	p-Value	LATE	p-Value
Dpp4 inhibitors and combinations	-.002	.862	-.023	**.043**	-.004	.720	.009	.700
Telmisartan/ Hydrochlorothiazide	-.002	.715	.008	.195	.009	.183	.010	.511
Voglibose	-.010	.139	.010	.148	.015	.052	-.014	.180
Olmesartan	-.004	.480	-.004	.557	.010	.133	-.006	.528

Table OA5.5 Regulated molecules: log(RuralRx%)

	Placebo 1		*Placebo 2*		*Placebo 3*		*Placebo 4*	
Molecule	LATE	p-Value	LATE	p-Value	LATE	p-Value	LATE	p-Value
Albendazole	.008	.591	.023	.142	-.009	.614	.004	.966
Amiodarone	.050	.731	-.118	.427	-.005	.977	.003	.969
Amlodipine	.045	.107	-.018	.521	-.046	.138	.006	.970
Atenolol	-.007	.699	-.019	.312	-.008	.707	.004	.984
Azathioprine	.101	.118	-.014	.836	-.058	.428	.002	.991
Cardiac glycosides	.030	.448	.017	.672	-.052	.236	.006	.963
Cetirizine	-.012	.179	-.015	.096	-.014	.140	.003	.979
Clopidogrel	-.041	.646	-.109	.225	-.186	.054	.018	.966
Enalapril	-.018	.628	.005	.903	.018	.664	.005	.955
Imatinib	.012	.652	-.053	**.038**	-.039	.158	.012	.958
Leflunomide	.164	.397	-.149	.451	-.086	.688	.013	.947
Losartan	-.093	.082	-.089	.098	.014	.808	.016	.964
Norethisterone	.041	.297	-.014	.729	.052	.227	-.001	.993
Olanzepine	.171	.052	-.109	.231	-.132	.188	.004	.964
Omeprazole	.001	.911	-.008	.315	.000	.998	.002	.986
Propranolol	-.078	.177	-.019	.755	-.018	.784	-.001	.998
Pyrazinamide	-.040	.314	-.008	.854	.008	.855	.008	.946
Trihexyphenidyl	.028	.725	-.019	.816	-.084	.342	.018	.948

Table OA5.6 Unregulated molecules: log(RuralRx%)

	Placebo 1		*Placebo 2*		*Placebo 3*		*Placebo 4*	
Molecule	LATE	p-Value	LATE	p-Value	LATE	p-Value	LATE	p-Value
Rabeprazole/Domperidone	.008	**.006**	.004	.156	-.001	.865	-.002	.702
Ranitidine	.000	.721	.001	.453	-.001	.548	.003	.265
Cefpodoxime	.004	.378	.017	.257	.003	.581	-.004	.385
Atenolol/Amlodipine	.001	.529	-.002	.218	-.001	.657	-.002	.360
Levetiracetam	-.002	.778	.005	.476	-.014	.086	-.004	.612
Gliclazide/Metformin	-.012	**.038**	-.012	**.048**	.000	.991	.011	.409
Aceclofenac/Paracetamol	.000	.845	-.002	.395	-.001	.654	-.002	.558
Levosulpiride/Rabeprazole	.003	.648	.002	.748	-.009	.175	-.013	.273
Cilnidipine	-.007	.838	.018	.593	-.014	.705	-.084	.577
Esomeprazole/Domperidone	.010	.074	.008	.184	-.001	.921	-.008	.089
Rosuvastatin/Fenofibrate	-.047	.242	-.012	.767	.005	.903	.235	.678
Esomeprazole	-.008	.228	.012	.094	.008	.285	-.011	.442
Terbinafine	.000	.875	-.002	.363	.003	.140	.004	.294
Fexofenadine	.014	.064	.010	.222	.003	.703	.008	.471
Atorvastatin/Aspirin	.009	.618	.000	.993	.026	.189	-.038	.278
Glibenclamide/Metformin	.003	.674	-.015	.053	-.014	.097	.001	.899

Online Appendix 6: Prices pre- and post-regulation

Regulated Molecule	Regulated price (Rs)	% price reduction[a]	LATE
Acyclovir	12.38	17.00%	.110
Amiodarone	6.93	24.70%	-.127
Amlodipine	3.01	9.20%	-.104
Atenolol	2.20	26.30%	-.117
Azathioprine	10.52	7.20%	-.010
Cefixime	11.96	3.90%	.086
Cetirizine	1.92	20.80%	.084
Clopidogrel	10.66	6.50%	-.145
Fluconazole	15.36	10.20%	.103
Glibenclamide	1.02	23.20%	-.091
Hydroxychloroquine	6.00	1.70%	-.257
Imatinib	93.13	.10%	.539
Isosorbide-5-mononitrate	3.50	.30%	-.069
Leflunomide	30.44	16.20%	-.086
Levothyroxine	1.18	8.20%	-.132
Metoprolol	3.59	5.70%	-.143
Norethisterone	5.39	13.60%	-.371
Olanzepine	3.08	8.90%	-.150
Omeprazole	3.21	32.50%	-.093
Ondansetron	5.06	12.50%	-.151
Others - Folic acid	1.46	48.70%	-.144
Propranolol	1.16	2.90%	.029
Pyrazinamide	7.35	2.50%	-.119
Sodium valproate	3.26	5.80%	-.087
Trihexyphenidyl	1.45	43.60%	-.162

Unregulated Molecule	(1)	(2)	(3)	%change[b]	%change[c]	LATE
Dpp4 inhibitors and combinations	239.90	239.90	239.90	.00%	.00%	.035
Glimepiride/Metformin	64.67	64.67	65.55	.00%	1.37%	.030
Pantoprazole/Domperidone	58.93	61.36	62.27	4.12%	1.48%	.061
Rabeprazole/Domperidone	81.13	81.29	81.29	.20%	.00%	.074
Ranitidine	13.64	13.64	13.87	.00%	1.63%	.162
Pantoprazole	82.40	85.09	85.09	3.26%	.00%	.037
Telmisartan/ Hydrochlorothiazide	104.08	104.08	104.71	.00%	.60%	.032
Atenolol/Amlodipine	37.61	38.44	39.28	2.20%	2.20%	.020
Levetiracetam	100.42	101.57	100.24	1.14%	-1.30%	.050
Omeprazole/Domperidone	40.69	43.03	43.67	5.73%	1.50%	-.016
Amlodipine/Telmisartan	67.34	64.29	66.50	-4.53%	3.44%	.038
Cefpodoxime/Clavulanate	171.88	171.33	176.04	-.32%	2.75%	.129
Aceclofenac/Paracetamol	30.24	30.24	30.39	.00%	.51%	.148
Ramipril	79.77	80.53	85.87	.96%	6.63%	-.063
Levosulpiride/Rabeprazole	125.21	125.21	125.21	.00%	.00%	.088
Dutasteride/Tamsulosin	143.85	148.05	150.77	2.92%	1.84%	.108
Esomeprazole/Domperidone	65.92	66.30	67.18	.57%	1.32%	.091
Rosuvastatin/Fenofibrate	134.32	133.85	137.06	-.35%	2.39%	.053
Levocetirizine	38.51	39.03	39.26	1.35%	.59%	.140
Esomeprazole	62.35	62.67	62.51	.52%	-.26%	.104
Terbinafine	129.22	114.60	115.90	-3.88%	1.14%	.157
Fexofenadine	71.52	71.52	74.51	.00%	4.17%	.161
Tamsulosin	112.76	112.76	113.74	.00%	.87%	.043
Glibenclamide/Metformin	20.66	20.90	22.20	1.14%	6.22%	.025

Notes:

(a) Weighted average price reduction of regulated molecules is based on the price change before and after regulation of the top 5 brands (with market share as weights)

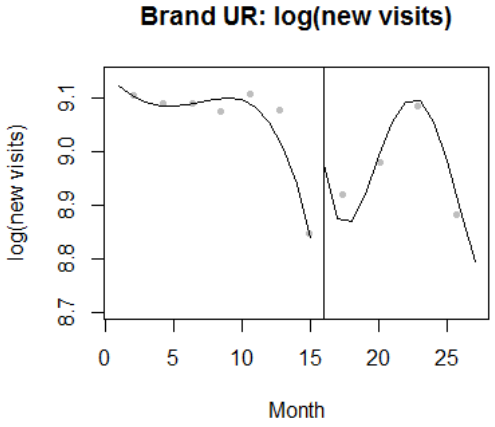
Average price of unregulated molecule in (1) March 2013 (before regulation), (2) June 2013 (just after regulation), and (3) December 2013 (6 months after regulation)

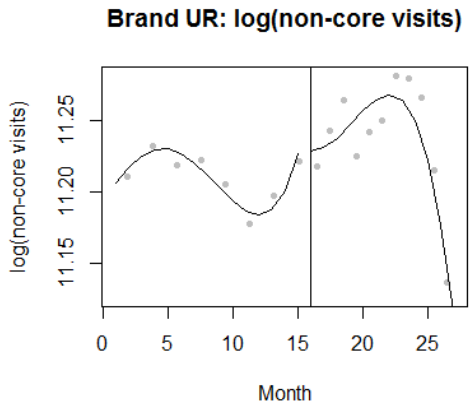
Average price of unregulated molecule computed as simple average of top 5 brands producing the molecule

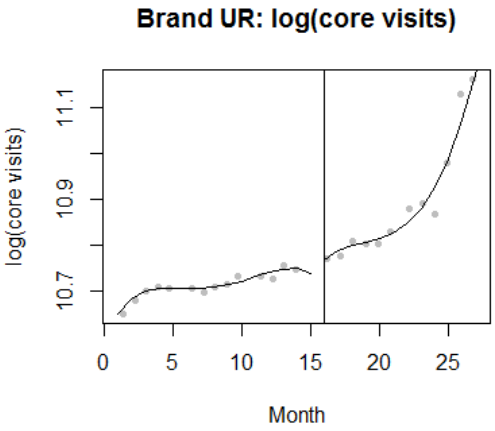
(b) % price change in June 2013 (relative to March 2013) (c) % price change in December 2013 (relative to June 2013)

Online Appendix 7: Detailing efforts: Brand UR and Brand R

a. Brand UR – Unregulated molecule







b. Brand R – Regulated molecule