Follow the Nudge but Hedge Your Risk: Physician Decision Making under Uncertainty

Abstract

During India's second wave of COVID-19, the government recommended Ivermectin for mild cases, potentially prompting a shift in physician prescribing behavior. This study examines how government policy directives can influence expert professional judgment in healthcare settings. Using individual-level prescription data and a difference-in-differences methodology, we analyzed prescribing patterns before and after the government directive. The study controls for heterogeneity across gender, location, physician specialty, and time. Results demonstrate that consulting and general physicians significantly increased Ivermectin prescriptions following the government recommendation (relative to other specialists), while dermatologists - the traditional prescribers for this drug - showed no change. Importantly, given the findings in the medical literature of the lack of effectiveness against COVID-19, physicians strategically managed risk by prescribing Ivermectin predominantly to younger, lower-risk patients. When the government withdrew its recommendation four months later due to efficacy concerns, prescriptions from these non-specialist physicians dropped sharply. Text analytics, randomized inference, and alternative control groups support these findings. Our research reveals that government nudges can compel healthcare professionals to revise their clinical beliefs and practices, even in high-stakes medical decision-making. These findings highlight the substantial influence of policy-driven behavioral change in public health contexts and underscore the potential risks of government directives during periods of clinical uncertainty. The lessons from our study are relevant to the current U.S. environment, where government agencies are taking strong positions on issues like vaccines.

Keywords: Healthcare; Decision-Making; Pandemics

JEL Codes: I18; D81

1 Introduction

Physicians' drug prescribing decisions are shaped by several factors, including the patient's clinical condition, pharmaceutical industry influence, physician characteristics, patient preferences, and medication costs (Ailawadi *et al.*, 2020; Davari *et al.*, 2018). Beyond these considerations, regulatory authorities frequently exert a significant impact on prescribing behavior, influencing clinical choices and occasionally prompting shifts in long-standing professional beliefs (Carrieri *et al.*, 2020; Kim, 2021). This study investigates how government regulation can alter drug prescribing patterns, particularly in periods of heightened uncertainty such as the COVID-19 pandemic.

The COVID-19 pandemic posed extraordinary challenges for healthcare systems globally, compelling governments to respond to rapidly evolving and unpredictable circumstances. In India, authorities implemented one of the world's most stringent nationwide lockdowns beginning March 24, 2020, in an effort to contain the virus's spread.[1] The country experienced two major waves of COVID-19 in 2020 and 2021 (see Figure A1), with the second wave proving especially devastating due to a higher mortality rate over a shorter period (see Figure A2).[2] Indian policymakers urgently sought solutions from around the world to mitigate the impact of the pandemic.

At this critical juncture, several studies began to suggest that Ivermectin - a drug traditionally prescribed by dermatologists for skin conditions - might be effective in treating the virus responsible for COVID-19 (Caly *et al.*, 2020; Kerr *et al.*, 2022; Kory *et al.*, 2021). Early laboratory and observational research indicated potential antiviral properties, and some clinical studies reported reductions in infection rates, hospitalizations, and mortality among users. However, major health authorities, including the World Health Organization (WHO)[3] and the European Medicines Agency (EMA)[4], issued advisories against the use of

[1]https://covidtracker.bsg.ox.ac.uk/stringency-scatter

[2]The first wave of COVID-19 was from April 2020 to January 2020, and the second wave was from March 2021 to June 2021.

[3]See report on 31st March 2021 - https://www.who.int/publications/i/item/WHO-2019-nCoV-therapeutics-2023.2

[4]https://www.ema.europa.eu/en/news/ema-advises-against-use-Ivermectin-prevention-or-treatment-

Ivermectin for COVID-19 outside of clinical trials. Both organizations cited insufficient and inconclusive evidence from clinical studies, as well as concerns about appropriate dosing and potential side effects at higher concentrations required for antiviral action. Their guidance emphasized that, despite some promising results, the overall quality and consistency of the available data did not support routine use of Ivermectin for COVID-19 patients.

This divergence in scientific opinion placed policymakers in a quandary. In the midst of increasing pressure on the healthcare system and a rapidly increasing death toll, the Indian authorities ultimately decided to recognize and recommend Ivermectin for the treatment of mild cases of COVID-19, reflecting the urgent need for therapeutic options during the peak of the pandemic.

Physicians tasked with treating patients with COVID-19 during the pandemic were influenced by three primary considerations: (i) their own understanding of Ivermectin's pharmacological profile, as well as rapidly evolving global research regarding its potential efficacy against COVID-19; (ii) the decision to prescribe Ivermectin carried a significant reputational risk, so physicians had to weigh the possible consequences of their choices, knowing that adverse outcomes could affect their position within the medical community and with patients; and (iii) the explicit endorsement of Ivermectin by government authorities.

Our objective in this study is to understand how physicians navigate these multifaceted decision environments, where clinical uncertainty, professional accountability, and regulatory guidance intersect. By examining physician responses to policy changes during a public health crisis, the research aims to deepen our understanding of medical decision-making under uncertainty. These insights are essential to inform future health policies and ensure effective management of emerging public health challenges.

To this end, we ask the following research questions: How do government signals influence decision making by professional service providers, specifically physicians? How do physicians balance the various considerations in responding to these signals? What are the implications for patients and policy makers? Using a unique dataset of Ivermectin prescriptions in India,

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covid-19-outside-randomised-clinical-trials we assess the effects of the government directive recommending the drug for individuals with mild COVID-19 (in home isolation). Our analysis centers on the prescribing behaviors of consulting and general physicians - who traditionally would not prescribe Ivermectin.

We first build a simple theoretical model that considers how government policy can influence professional decision-making. We propose that the government's explicit endorsement of Ivermectin lowered the perceived risks and costs for physicians associated with prescribing the drug for COVID-19. As a result, we hypothesize that this policy intervention can lead to a increase in Ivermectin prescriptions among consulting and general physicians, reflecting a shift in clinical practice driven by regulatory cues.

Using a difference-in-differences approach, we find that consulting and general physicians (our "treatment" group) prescribed significantly more Ivermectin pills than other physician groups (our "control" group) - during India's second COVID-19 wave. Both the frequency of Ivermectin prescriptions and the average dosage per patient increased among these physicians following the government directive.

Further analysis reveals that this "surge" in prescribing was predominantly driven by increased prescriptions for *younger patients*. Physicians appeared to strategically manage clinical risk by favoring younger individuals, who are generally less susceptible to comorbidities and thus perceived as lower risk. This risk-hedging behavior suggests that, while physicians responded to the government's nudge by shifting away from standard cold and flu treatments toward Ivermectin, they did so with caution, prioritizing patients with a lower likelihood of adverse outcomes.

Importantly, these patterns were not observed during the first wave of COVID-19, when no government endorsement for Ivermectin existed. The absence of similar prescribing trends in the earlier period underscores the pivotal role of policy directives in shaping clinical practice during the pandemic.

We then applied text analytics to patient complaints associated with Ivermectin prescriptions and observed a marked shift in the nature of reported symptoms. Prior to the second COVID-19 wave, keywords in patient complaints predominantly referenced dermatological issues such as itching, lesions, and rashes. However, during the pandemic, the primary keywords shifted to respiratory symptoms including cough, fever, and sore throat (See figure 1 for the word cloud).

We implemented several robustness checks; confirming the absence of pre-treatment trends and spillovers to dematologists. We conducted a permutation-based randomized inference test, which indicated that the observed treatment effects are unlikely to be due to chance. We also examined prescription patterns following the *withdrawal* of official support for Ivermectin. The effect dissipated once the government retracted its recommendation, reinforcing the conclusion that policy guidance was the primary driver of prescribing behavior change.

Physician preferences have the potential for societal impact by affecting healthcare costs (Bodnar *et al.*, 2024), patients' quality of life (Gramelspacher *et al.*, 1997), and access to healthcare (Li *et al.*, 2017). Uncontrolled prescriptions in the past have caused opioid crises (Kim, 2021; Rothstein, 2017)[5], antibiotic resistance (Ventola, 2015), and vaccine hesitancy (Chervenak *et al.*, 2022).

The findings from our study underscore the influence that government signals can have on physician behavior. This behavior is especially pronounced in high-stakes scenarios where conclusive scientific evidence is lacking, and physicians must balance patient care with reputational concerns. Health authorities must recognize that regulatory communications not only inform practice but can actively reshape clinical norms. Policymakers should thus ensure that such directives are grounded in robust, transparent, and up-to-date evidence, and that mechanisms are in place to quickly revise guidance as new data emerges. Doing so can mitigate downstream consequences such as inappropriate prescribing or public distrust in healthcare institutions.

In addition, the study highlights the importance of designing regulatory interventions that anticipate strategic adaptations by professionals. The selective prescription of Ivermectin to younger, lower-risk patients demonstrates how physicians may internalize policy guidance

[5]https://www.wsj.com/health/healthcare/medicare-opioids-overdose-doctor-9b7d49d1

while also hedging against potential risks. This suggests that policies should be complemented with implementation support and educational outreach that equips physicians to interpret and apply recommendations appropriately across patient profiles. Ultimately, the lessons from this case extend beyond the COVID-19 context, offering valuable guidance for crafting effective policy responses to future public health emergencies - where timely action must be balanced with scientific caution and stakeholder engagement.

The lessons from our study are relevant to the current U.S. environment, where government agencies are taking strong positions on issues like vaccines and processed foods. And just like Indian physicians, we expect physicians in the US to face similar pressures: balancing personal clinical judgment, rapidly changing evidence, professional reputation, and legal liability in the face of government guidance on controversial topics such as vaccine mandates or "acceptable" processed food ingredients. To that extent, we believe that our study context generalizes to other such settings.

Related Literature:

Physicians are one of the most explored individual professionals in healthcare marketing literature. This literature covers the aspects such as physicians decision making under uncertainty (Dai & Singh, 2020) and how pricing and promotional activities influence prescription choice behavior (Gönül *et al.*, 2001; Fischer & Albers, 2010). Studies have shown influence of artifical intelligence in physicians's prescription behaviour (Dai & Singh, 2025) and how physicians resolve uncertainty about the drug prescription through firms marketing activities and patients' experiences choices (Chintagunta *et al.*, 2012)

Studies have shown impact of competition (Gaynor *et al.*, 2015), publicity (Ching *et al.*, 2016), television advertisement (Shapiro, 2018, 2022), direct to consumer advertisement (Amaldoss & He, 2009) and technological advances (Agarwal *et al.*, 2020) on decision making in health care markets.

There exists literature in marketing science that delves with consequences of government regulations on healthcare markets. Studies have shown the effect of price control orders by government on the availability of life-saving drugs (Jaikumar *et al.*, 2024), the impact that a ban on menthol-flavored cigarettes can have on the health and economics of a state (Goli *et al.*, 2024), how rules like industry payment disclosure affect physician prescription behavior (Guo *et al.*, 2020), and the effect of regulatory frameworks on healthcare marketing (Moorman *et al.*, 2024). By demonstrating how government regulation can rapidly reshape physicians' prescribing behaviors during a public health crisis, our study adds to this literature by highlighting the power of non-market forces - particularly regulatory nudges - in influencing professional decision-making.

2 Background

Ivermectin oral tablets are used worldwide at precise doses to treat certain parasitic infections (Lind *et al.*, 2021). Ivermectin topical (on the skin) formulations cure head lice and skin conditions like rosacea. In the early stages of COVID-19, an in vitro study had shown that Ivermectin inhibits the replication of SARS-CoV-2 in tissue cell cultures (Caly *et al.*, 2020). Another study based on 18 RCT trials of Ivermectin found significant reductions in mortality and time to recovery from COVID-19 (Kory *et al.*, 2021). Thus, the drug mainly responsible for curing skin diseases looked beneficial for curing COVID-19.

Contrary to such research, there were multiple reports by the WHO[6] and the European Medical Agency[7] that advised against using Ivermectin for patients with COVID-19.

Given pandemic pressures, the government of India preferred to follow reports that favored Ivermectin. Policymakers were desperately looking for some solution to tackle the deadly COVID-19 second wave. Indian Council of Medical Research (ICMR)[8] passed a directive recognizing Ivermectin for mild cases and home isolation. However, four months later, ICMR issued notice to consider the exclusion of Ivermectin from the clinical guidance of adult COVID-19 patients. In September 2021, the Health Ministry of India removed the usage of Ivermectin from its approved COVID-19 health guidelines. Figure 2 shows a detailed

[6] See report on 31st March 2021 - https://www.who.int/publications/i/item/WHO-2019-nCoV-therapeutics-2023.2

[7] https://www.ema.europa.eu/en/news/ema-advises-against-use-Ivermectin-prevention-or-treatment-covid-19-outside-randomised-clinical-trials

[8] Apex body responsible for combating the COVID-19 pandemic in India.

timeline of these events. Studies have now emphatically demonstrated that treatment with Ivermectin did not result in a lower incidence of medical admission to a hospital due to the progression of COVID-19 (Reis *et al.*, 2022). A lot of past research in favor of Ivermectin use for COVID-19 is now being retracted or questioned.

To see whether Ivermectin had any impact on COVID-19 in India, we plot the number of Ivermectin pills prescribed by physicians in different states on the map, and on the other side, we map the number of deaths in these states. As shown in figure B3, we see no relationship between the number of Ivermectin pills prescribed and the number of deaths. We also perform a regression analysis to find no correlation between prescribed Ivermectin pills and any reduction in COVID-19 cases or deaths (See table B3).

Researchers have claimed different reasons for this swift uptake of Ivermectin. There have been reports on Ivermectin frenzy being driven by anti-vaccine activists who found takers in vaccine-hesitant people and people desperate to treat loved ones suffering from the virus.[9] We checked how the search for word 'Ivermectin' trended on Google in different countries (See figure B1). We find that the earliest Ivermectin usage trends against COVID-19 started in Brazil in the early 2020s. The choice of Iveremctin was driven by anti-vaccine rhetoric or vaccine hesitancy (de Arruda Castro & Reich, 2024). Google's search trend for Ivermectin searches picked up in early 2021s in South Africa as they faced their second wave. As shown in the figure, India and the US were rather late followers of the Ivermectin trend.

Barnett *et al.* (2022) claimed that an increased prescription of Ivermectin was associated with political voting patterns in the 2020 US presidential election. Temple *et al.* (2021) showed a 24-fold increase in Ivermectin prescriptions in the United States in August 2021 compared to same month last year. Chua *et al.* (2022) estimated that 2.5 million dollars were spent on Ivermectin in just one week of August 2021, claiming it to be wasteful insurer spending. There have also been claims that Ivermectin was promoted by telehealth sites that had ties with right-wing groups in the US for their own vested interests.[10] Thus, there have

[9]https://www.theguardian.com/world/2021/sep/13/Ivermectin-treatment-covid-19-anti-vaxxers-advocates

[10]https://www.theguardian.com/world/2021/sep/13/Ivermectin-treatment-covid-19-anti-vaxxers-advocates

been questions about the prescription of Ivermectin and its welfare impact worldwide.

3 Theoretical Model & Hypothesis Building

We use a simple government-physician theoretical model in which the physician's actions are not directly observable. The government wishes to design a policy for physicians to provide a "cure" to the maximum number of patients infected by COVID-19. On the other hand, a physician rationally wants to make a choice that maximizes their utility given the effort and cost involved in consulting a patient.

To simplify the analysis, we make the following assumptions. We assume that only a finite number of patients can be cured in a certain time. We also assume that all doctors are working in government hospitals and directly or indirectly report to the government. There are only two types of patients: old and young. Old patients represented by x_{o1}, x_{o2}...., x_{on} and young patients represented by x_{y1}, x_{y2}...., x_{oyn}. The physician can take two actions, a or b, which correspond to prescribing a drug a or drug b. Prescribing Ivermectin can be considered one of the two actions taken by the physician to provide a cure to COVID-19-infected patients. The chosen action would influence the probability of how many patients can be cured by the doctor. Thus π_{ia} is the probability that x_i patients are cured if the doctor prescribes drug 'a'. Similarly, π_{ib} is the probability that x_i patients are cured if the doctor prescribes drug 'b'.

Let $s_i = \mathrm{s}(x_i)$ be the payment from the government to the physician for catering to x_i patients. Then the expected benefit for the government if the physician chooses drug b, say, is

$$\sum_{i=1}^{n}(x_i - s_i)\pi_{ib} \tag{1}$$

The physician is a risk-averse individual who wishes to maximize the utility function of the payment $u(s_i)$ while considering the cost of his action, c_b, i.e. cost of prescribing drug 'b'. The costs for the physician can be reputation costs, which she may lose if the drug is ineffective. There is also a chance of attrition of loyal patients if the prescribed drug turns out to be harmful. Hence, the physician will choose a drug b over drug a if the utility received from prescribing drug b net of its costs is greater than that from prescribing drug a. This is shown mathematically in the equation below.

$$\sum_{i=1}^{n} u(s_i)\pi_{ib} - c_b \geq \sum_{i=1}^{n} u(s_i)\pi_{ia} - c_a \tag{2}$$

There can be a case in which the physician may not engage with the patient at all. This was quite prevalent during COVID-19 as some physicians, concerned for their safety, didn't see any patients. Suppose that if the physician doesn't participate, she gets utility $\bar{u}$. Hence, the expected utility from participation and prescribing drug b will be

$$\sum_{i=1}^{n} u(s_i)\pi_{ib} - c_b \geq \bar{u} \tag{3}$$

The government wants to maximize equation 1 subject to constraints mentioned in equation 2 and 3. Note that both the government and physicians are making optimal choices in this matter. The physician is going to choose a drug that is best for her, given the incentive system (s_i) set up by the government and the costs involved in prescribing that drug. Understanding this, the government wants to offer a pattern of incentives that cure the most number of patients. Effectively, the government chooses the action that it desires for the physician, taking into account the cost of doing so.

We set up the lagrangian for the maximization problem using equation 1, 2 and 3.

$$\mathcal{L} = \sum_{i=1}^{n}(x_i - s_i)\pi_{ib} + \lambda\left(\sum_{i=1}^{n} u(s_i)(\pi_{ib} - \pi_{ia}) - c_b + c_a\right) + \mu\left(\sum_{i=1}^{n} u(s_i)\pi_{ib} - c_b - \bar{u}\right) \tag{4}$$

Here, both λ and μ are positive. Differentiating this expression with respect to s_i gives us

$$-\pi_{ib} + \lambda u'(s_i)[\pi_{ib} - \pi_{ia}] + \mu u'(s_i)\pi_{ib} = 0$$

Rearranging this, we get

$$\frac{1}{u'(s_i)} = \mu + \lambda\left[1 - \frac{\pi_{ia}}{\pi_{ib}}\right] \tag{5}$$

Recall that π_{ia} is the probability of curing x_i patients when the physician prescribes drug a. If we assume that $\pi_{ia} = \pi_{ib}$[11], then the second term on the right-hand side in equation 5

[11] This is a fair assumption as due to uncertainties during COVID-19, no one was sure about which drug would provide absolute care.

becomes zero, and then $u'(s_i)$ is equal to some constant $1/\mu$. This means that payment to the physician is independent of the patients that he cures. Thus, s_i is equal to some constant $\bar{s}$. Substituting this into equation 2 we find that

$$u(\bar{s})\sum_{i=1}^{n}\pi_{ib} - c_b \geq u(\bar{s})\sum_{i=1}^{n}\pi_{ia} - c_a$$

Since $\sum_{i=1}^{n}\pi_{ib}$ and $\sum_{i=1}^{n}\pi_{ia}$ are summations of probabilities and hence are equal to 1, we get

$$c_a > c_b \tag{6}$$

This means that, under all the assumptions, a physician would prefer to prescribe drug b only if the cost of prescribing drug a is higher than the cost of administering drug b.

In our case, we consider drug b as Ivermectin and drug a as any other individual drug or its combination. The government of India passed a directive in April 2021 that mentions that Ivermectin may be used for those with mild cases and in home isolation. The purpose of this renewed directive was to cater to briskly increasing COVID-19 cases during the second wave in India. The directive was publicly available to both patients and physicians. We believe that the presence of this directive would have significantly reduced the fear of patient attrition and reputation costs. Thus consulting and general physicians who were primarily responsible for handling COVID-19 patients increased their prescription of Ivermectin to cure COVID-19. This leads us to our first hypothesis.

Hypothesis 1 *Owing to the new directive from the government, the prescription of Ivermectin by consulting and general physicians increased compared to other doctors during the COVID-19 second wave.*

We also wish to study if there was heterogeneity among the patients to whom Ivermectin was prescribed. We know there were existing international studies that showed no effect of Ivermectin. Also, WHO, European Medical Agencies, the US FDA, and Merck (the company that manufactured Ivermectin) were fairly against the use of Ivermectin, and enough of this information was available in March 2021. Physicians would have been aware of these reports, but they were still prescribing Ivermectin because of the support received from the Union Health Ministry's medical guidelines, as shown in hypothesis 1.

In such a scenario, when physicians knew that there was a certain risk involved, they would prefer to prescribe the drug to patients who were at low risk. Also, administering it to low-risk patients would further reduce the reputation cost or attrition cost of prescriptions by physicians. In our model, we have two types of patients: young (x_{yi}) and old (x_{oi}). Existing comorbidity makes the cost of treating older patients higher. Thus, extending equation 6, we get

$$\text{If } c_a[x_{yi}] > c_b[x_{yi}]$$

$$\text{then, } c_a[x_{oi}] >> c_b[x_{oi}]$$

Thus, physicians would prefer to prescribe a risky medicine to younger patients than older patients to further reduce costs. This leads to our second hypothesis.

Hypothesis 2 *Prescription of Ivermectin to younger patients should be higher as compared to older patients during the second wave of COVID-19.*

We further wish to understand why Ivermectin prescription was not so high in the first wave of COVID-19 in India. To understand it theoretically, we go back to our agency theory model where we set up the lagrangian in equation 4. We now differentiate this equation with respect to c_a and c_b to get

$$\frac{\partial \mathcal{L}}{\partial c_a} = \lambda \tag{7}$$

$$\frac{\partial \mathcal{L}}{\partial c_b} = -(\mu + \lambda) \tag{8}$$

We know that λ and μ are positive values. According to equation 7 and 8, a slight decrease in the cost of the chosen drug b always increases the government's utility by a more significant amount as compared to an increase of identical magnitude in the cost of drug a.

The government of India removed other frequently used drugs like hydroxychloroquine (HCQ) and antibiotics like azithromycin from their directive to cure COVID-19 patients. This would undoubtedly have increased the cost of usage of these drugs by physicians to cure COVID-19 as the risk of prescribing them increased. However, this increase in the cost of other drugs was not enough for an increase in the prescription of Ivermectin during the first wave. It was only when Ivermectin's usage was recommended by the government, in its directive that came at the start of the second wave, that the cost of its usage by the physicians was reduced. This leads to our third hypothesis.

Hypothesis 3 *Compared to the increase in the prescription of Ivermectin during the second wave of COVID-19 in India, there was no significant change during the first wave.*

In the next section, we evaluate these hypotheses empirically.

4 Data & Methods

We obtained data on Ivermectin drug prescriptions from Healthplix[12] from 2019 to 2021. The dataset provides information on drug prescriptions like dosage frequency, number of prescriptions, dosage duration, and prescription month. We have information on the doctor's specialty and the patient's age, gender, and the state of India to which he/she belong. For our text analysis, we also have keywords related to complaints of the patients to whom Ivermectin was prescribed.

Using the information on the prescription of drugs, we create a variable that describes an ideal number of pills prescribed. This is constructed as a multiplication of the number of prescriptions, dosage frequency, and dosage duration. Detailed descriptions of all variables are provided in table 1. Summary statistics of the variables are presented in table 2.

4.1 Difference-in-Differences (DID)

We use the DID method to evaluate the impact of COVID-19 on the change in the prescription of the Ivermectin drug by consulting and general physicians. Our treatment group comprises consulting and general physicians, and the control group comprises physicians with all other specialties.[13] Since we are analyzing the impact of the second wave of COVID-19 in India

[12] HealthPlix is India's largest EMR trusted by 14,000+ doctors across 16 specialties. Multiple recent papers have used Healthplix's EMR data to analyse patient and physician-related questions in their research (Jayanthy *et al.*, 2024; Shao *et al.*, 2023)

[13] We perform robustness checks with alternate control group in the next section.

that started in March 2021, the data sample we use for analysis is from November 2020 to June 2021. This ensures an equal period of four months before and after the shock.

Table 3 provides descriptive estimates from the DID framework showing general physicians' change in Ivermectin prescription post-COVID-19 second wave. The table highlights the mean value of the number of pills prescribed in the pre- and post-period for consulting and general physicians and rest specialists. We define November 2020 to February 2021 as the pre-shock period and March 2021 to June 2021 as the post-shock period. The estimates from the first difference indicate a significant increase in the number of pills prescribed by consulting and general physicians post-COVID-19 second wave in India. Table 3 also highlights raw means' DID estimate (first minus second difference). The t-test and the p-values confirm the significance of the mean difference. These preliminary results suggest an increase of, on average, 3.554 Ivermectin pills prescribed by general physicians post-COVID-19 second wave compared to physicians with other specialties. This is a 39.06% increase in prescription when compared with the mean (9.098) of our sample. We believe these results, though important, are merely suggestive and need to be controlled for time variant unobserved heterogeneities at the physician and patient level. We would also need robustness checks to strengthen our identification strategy to establish a stronger causal inference.

4.2 Empirical Strategy

We estimate the average treatment effect of the COVID-19 pandemic on the number of Ivermectin pills prescribed by consulting and general physicians compared with other physicians. To study the causal relation, we use the below-mentioned DID specification as our identification strategy.

$$\mathbf{y_{saglt}} = \beta_0 + \beta_1 \mathbf{Physician_s} \times \mathbf{CovidWave_t} + \theta_s + \phi_a + \gamma_g + \eta_l + \delta_t + \alpha + \epsilon_{saglt} \tag{9}$$

Where y_{saglt} is measured at the specialization-age-gender-location-month level, y_{saglt} is the number of pills prescribed by a doctor with a particular specialization to an individual of a specific age and gender belonging to a certain state location in a month. $Physician_s$

corresponds to doctors in our treatment group, coded as one for doctors specializing as consulting and general physicians and zero for doctors from other specializations (control group). $CovidWave_t$ equals one if the month in which the patient received the prescription lies from March 2021 to June 2021, zero otherwise. θ_s, ϕ_a, γ_g, η_l and δ_t represent Specialty, Month, Gender, Age and Location Dummies respectively. α represents all possible paired dummies. These dummies allow us to control for observed or unobserved heterogeneity at different levels.

The central coefficient of interest in our study is β_1. This estimate captures the effect of COVID-19's second wave on the prescription of Ivermectin drug by consulting and general physicians compared to other physicians. In other words, it measures how changing government regulations post the second wave of COVID-19 in India caused consulting and general physicians to alter their positioning of drug prescriptions.

5 Findings

5.1 Baseline Results (H1)

Table 4 presents our baseline results by estimating equation 9. The dependent variable in all the columns is the number of pills physicians prescribe. Column (1) shows baseline estimations without any fixed effects. Column (2) includes individual dummies for month, state, gender, age, and doctor specialty. Column (3) includes all possible paired dummies, and in column (4), we change the dependent variable to a logarithm of the number of pills prescribed. Robust standard errors are estimated in all models.[14]

The interaction coefficient in table 4 represents the impact of the second wave of COVID-19 on the number of pills prescribed by consulting and general physicians compared to physicians from other specialties. We use columns (3) and (4) for interpretation since it is the most conservative with all fixed effects. In column (3), we find a positive and significant interaction coefficient (β = 2.613). This indicates that government intervention during

[14] We also collapse the data at the Specialty-Location-Time level. All results hold the same sign and significance as the baseline. Results for the same are shown in table B4.

COVID-19 caused, on average, an increase of 2.613 pills prescribed by consulting physicians compared to other physicians. Column (4), where the dependent variable is a log of the number of pills prescribed, indicates a 16.9% increase in the number of pills prescribed by consulting and general physicians compared to others post-second wave. The effect of the government nudge, causing a change in behaviour amongst citizens and physicians, has been studied by researchers (DellaVigna & Linos, 2022; Munir *et al.*, 2022). Our DID estimate of 16.9% change from the control group is in line with these studies.

5.2 Non-Existing Pre-trends

The DID approach provides causal estimates based on the "parallel trends" assumption. This implies that without a second wave of COVID-19 and the government intervention that followed, the outcomes for the consulting and general physicians and other specialty physicians would have followed parallel trajectories over time. To evaluate the parallel trend assumption, we check if there are existing pre-trends between the treatment and control group following Angrist & Pischke (2009). The model mentioned below estimates the interaction coefficient using an event study design.

$$y_{saglt} = \beta_0 + \sum_{t=Dec'20}^{Jun'21} \beta_t \, Treated + \theta_s + \phi_a + \gamma_g + \eta_l + \alpha + \epsilon_{saglt} \tag{10}$$

Month t varies from December 2020 to June 2021. The first month in our data sample, November 2020, is the baseline in this regression. We plot the coefficients obtained from the above equation. In our estimated results, insignificant coefficients in the pre-period (till February 2021) would satisfy the assumption of parallel trends between the treatment and control group.

In figure 3, where the dependent variable is the number of pills prescribed, we find that the coefficients in the pre-treatment period are near zero and insignificant. This indicates that in the absence of the treatment, the outcome for the control and treatment groups shall follow a parallel trend. Notably, the figure shows significant positive coefficients for the months following the COVID-19 shock in March 2021. This suggests that compared to other physicians, there was a significant increase in the prescription of Ivermectin pills by consulting and general physicians in India.

5.3 Prescription and Dose Frequency

The total number of pills prescribed is a variable created by us, which is a multiplication of the prescription, dosage frequency, and duration. To ensure that the multiplication effect is not driving our results, we separately analyze the prescription and dosage frequency as individual variables.[15] In table 5 we estimate these results using equation 9. The dependent variable in columns (1) and (2) is the dose frequency, and in columns (3) and (4) is the prescription count.

As seen in table 5, interaction coefficients in all columns are positive and significant. Columns (1) and (3) show the baseline results without any fixed effects. Columns (2) and (4) are the most saturated results with all fixed effects, and thus, we use these coefficients for interpretation. In column (2), we find the positive and significant interaction coefficient ($\beta = 0.024$), which is a 2.04 % increase from the average sample mean prescriptions of 1.178. Similarly, In column (4), we find the positive and significant interaction coefficient ($\beta = 0.331$). This is a 21.12 % increase from the average sample mean prescriptions of 1.567 (See table 2). Thus, the results show a significant increase in both dosage frequency and prescription count by consulting and general physicians as compared to the rest of specialists post pandemic.

5.4 Higher Prescription to Younger Patients (H2)

As described in our theoretical model in section 3, the physician is following the instructions from the government but is also required to hedge the risk. The consulting and general physicians are increasingly prescribing the Ivermectin drug as suggested by the government. But at that time, Ivermectin was not considered a foolproof remedy for COVID-19, and doctors must have been aware of this. As shown in figure 4, to hedge the risk, physicians

[15]We don't analyze the duration variable separately as it is mostly fixed to one week or two weeks as part of a doctor's prescription and thus doesn't have enough variation.

strategically reposition the drug administration and prescribe it more to young patients. A simple reason could be that the likelihood of fatal loss is lower in younger people as they have lower comorbidity.

To test this hypothesis, we continue with our DID framework. This time, the treatment group is younger patients aged less than 60 (or aged 45 in a different model), and the control group is older patients. We use the specification below for our estimation.

$$\mathbf{y_{saglt}} = \beta_0 + \beta_1 \mathbf{YoungPeople_a} \times \mathbf{CovidWave_t} + \theta_s + \phi_a + \gamma_g + \eta_l + \delta_t + \alpha + \epsilon \quad (11)$$

where y_{saglt} is measured at the specialization-age-gender-location-month level. y_{saglt} is the number of pills prescribed by a doctor with a particular specialization to an individual of a particular age and gender belonging to a particular state location in a month. $YoungPeople_a$ corresponds to patients in our treatment group, which equals one if the age of the patient is less than 60 (or aged 45 in a different model) and zero for older patients (control group). $CovidWave_t$ equals one if the month in which the patient received the prescription lies from March 2021 to June 2021, zero otherwise. θ_s, ϕ_a, γ_g, η_l and δ_t represent Specialty, Month, Gender, Age and Location Dummies respectively. α represents all possible paired dummies.[16]

The main coefficient of interest in our study is β_1. This estimate captures the effect of the COVID-19 second wave on the prescription of Ivermectin drugs to younger patients compared to older patients. In table 6 we estimate these results using equation 11. The dependent variable in all three columns is the number of Ivermectin pills prescribed. Column (1) shows the baseline effect without any controls. In column (2) we introduce the individual dummies. In column (3), we introduce paired dummies along with individual dummies. In column (4), we reduce the age of the treatment group to less than 45 instead of 60, as used in the first three columns, and apply all fixed effects.

We use the fully saturated model in column (3) for our interpretation. We find a positive and significant interaction coefficient ($\beta = 1.805$). This indicates that government intervention during COVID-19 caused, on average, an increase of around 1.8 pills prescribed

[16]Before we analyze our regression coefficient, we ensure the non-existence of pre-trends for this specification. Results of the same are shown in figure B2.

to younger patients as compared to older patients. This is a 19.83% increase in the number of pills prescribed when compared to the average of 9.098 pills of Ivermectin prescribed by any physician. As shown in column (4), the interaction coefficient has the same sign and significance even when we reduce the age of the treatment group to 45.

5.5 No effect during COVID-19 First Wave (H3)

Until now, we have been exploring the results of the increased use of Ivermectin when India was undergoing the second wave of COVID-19. It is essential to know if a change was seen during the first wave when there was no government directive in favor of Ivermectin.

In table 7, we estimate the change in the number of Ivermectin pills prescribed post-first wave of COVID-19 in India. We use the same equation 9 for estimation but change the time frame. The first wave of COVID-19 started in April 2020 in India. We, therefore, take a sample from January 2020 to July 2020 to include equal pre and post-period for evaluation. The dependent variable in all cases is the number of Ivermectin pills prescribed. In columns (1) and (2), we estimate the impact of COVID-19's first wave on a number of pills prescribed by consulting and general physicians. In columns (3) and (4), we estimate the effect of the first wave of COVID-19 on Ivermectin pills prescribed to younger people.

Columns (1) and (3) show baseline effects without controls. Columns (2) and (4) include all possible fixed effects. We can see that all the interaction coefficients are either insignificant or negative. This suggests no impact on Ivermectin pills prescription during the first wave of COVID-19 in India. As shown in timeline figure 2, studies existed before the first wave that showed that Ivermectin could be effective. Still, the physicians didn't change their positioning since there was no government directive in favor of Ivermectin like the one during the second wave.

6 Robustness Checks

6.1 Text Analytics

The dataset also provides the keywords corresponding to the complaints of the patients to whom Ivermectin was prescribed. As a start, we created a word cloud of the complaints of patients who were administered the Ivermectin drug. Figure 1 shows how the same drug prescribed for itching and lesions is prescribed for cough and fever post-COVID-19 second wave in India. The drastic change in keywords, in a way, reassures our empirical results that physicians repositioned their drug prescriptions.

We perform topic modeling to further make a robust claim on the changing text of patient claims. We use a Latent Dirichlet Allocation (LDA) technique, which is an unsupervised way to identify hidden topics within the text.[17] LDAGIBBS command in STATA 15 is used to obtain clustered keywords along with word probability. All this is done without predefined, explicit dictionaries or interpretive rules. In table B1, we show the outcome of the topic modeling exercise. We find five topics and the prominent keywords that are covered under those topics. Topic 1 and topic 2 highlight the presence of COVID-related keywords.

We empirically examine the change in probability of topic 1 and topic 2 related keywords in patient complaints when the Ivermectin drug was administered by consulting and general physicians post-COVID second wave. We use the same baseline equation 9 with the probability value of topic 1 and topic 2 keywords combined as the dependent variable. Table 8 shows results from our estimation. Column (3) comprises all possible individual and fixed effects. The positive and significant interaction coefficients suggested an increase in COVID-19-related complaints when Ivermectin was prescribed by consulting and general physicians post-COVID-19 second wave compared to doctors with another specialty.

[17] Recent prior work has used topic modeling to determine an increase in AI in patents (Rathi *et al.*, 2024b) and change in restaurant reviews post COVID-19 (Rathi *et al.*, 2024a).

6.2 No Spillover of Prescriptions with Dermatologists

As shown in figure 5 dermatologists were the major prescribes of Ivermectin in the pre-COVID era. There could be a concern of overlap or spillover of prescriptions between consulting/general physicians and dermatalogists, where COVID-19 patients could have gone to dermatologists knowing they would prescribe Ivermectin. We rule out this concern in three ways.

First, we conduct a sub-sample analysis where the control group comprises only dermatologists. Thus, they can be considered as the ideal control group among all physicians. Results in column (1) of table 9 show the findings with dermatologists as the control group using equation 9. We find that interaction coefficient remain positive and significant even with a stringent sub-sample analysis.[18] Second, we repeat our baseline analysis but this time removing dermatologists from the control group. As we see in column (2) of table 9 the coefficient is positive and significant and is similar in magnitude as baseline result. Third, as shown in figure 6, prescription by dermatologists remains fairly constant pre-and post the second wave of COVID-19. To check it empirically we keep dermatalogists as treatment and all other specialities in control group and find no-significant change in their number of prescriptions as shown in column (3) of table 9.

In sum, using all the three analysis we can conclude that prescription by dermatologists did not change during COVID-19 and there was no spillover between prescriptions by consulting/general physicians and dermatalogists.

6.3 Randomized Inference Test

We utilize a falsification exercise named randomized inference test to assess if the change in the number of Ivermectin pills prescribed by consulting and general physicians is just a matter of chance. Originally developed by Fisher (1936) and taken forward by Rosenbaum (2002) to perform tests for experiments, randomized inference is increasingly being applied

[18] We repeat the sub-sample analysis with the top 5 specialists - cardiologists, dermatologists, diabetologists, endocrinologists, and pulmonologists as a control group. We find all the results hold the same as the baseline. Results of the same are shown in table B5.

to non-experimental data (Agrawal *et al.*, 2024; Nagler *et al.*, 2020). We use the 'ritest' command developed by Heß (2017) in STATA to conduct the randomized inference test.

We compare the coefficients from our baseline specification shown in column (1) in table 4 to a distribution of coefficients. We follow a three-step process. First, we reallocate the treatment and control groups randomly, ensuring that we match the sample size with our baseline model. Second, we use the baseline specification equation 9 to estimate the treatment effect using these reallocated treatment and control groups. Third, we repeat this exercise 500 times. The idea is to compare the coefficients we obtain from this random allocation to those from our baseline specification. Figure 7 shows the density distribution of all interaction coefficients obtained after the randomization. The vertical red line is the coefficient that we obtain in column (1) in table 4. One can see that almost none of the random allocation generated coefficients can cross our coefficient. The p-values obtained from the randomized inference test are shown in table B2. The p-values suggest that the effects of COVID-19 on the change in the number of prescriptions of Ivermectin by consulting and general physicians are unlikely to be observed just by chance.

6.4 Effect Disappears as Government Retracts its Directive

In this section, we provide evidence that shows the impact of government directives on consulting and general physicians to prescribe Ivermectin. As shown in figure 2, in August 2021, the ICMR issued a notice to 'Consider Exclusion of Ivermectin' from clinical guidance of adult COVID-19 patients. We look for the impact of this directive on the prescription of Ivermectin by consulting and general physicians. We consider the sample of August 2021 to December 2021 for this analysis.

As shown in table 10, we find for all three dependent variables, the prescription of Ivermectin by consulting and general physicians is either negative or insignificant compared to the rest of the specialists. This result shows that the government directive highly influenced consulting and general physicians' decision-making as we find a quick spike and then fading of prescriptions (See figure 6) based on the directive.

7 Discussion and Conclusion

Decision-making under uncertainty, especially in healthcare, when lives are on the line, has higher stakes and is riskier. This study finds that government policy can significantly alter professional behavior even under conditions of scientific uncertainty. Following the Indian government's directive endorsing Ivermectin for mild COVID-19 cases during the second wave, consulting and general physicians - who historically did not prescribe the drug - showed a substantial increase in prescriptions. A difference-in-differences analysis confirms a statistically significant rise in both the frequency and dosage of Ivermectin prescriptions relative to other specialists, with a 16.9% increase attributed to the policy intervention. Importantly, physicians appeared to hedge risk by prescribing the drug predominantly to younger, lower-risk patients. No such pattern was observed during the first wave when the government had not yet issued a directive. Further robustness checks, including randomized inference tests, text analytics of patient complaints, and alternative control groups, all support the core findings. Once the policy was withdrawn, Ivermectin prescriptions by these physicians sharply declined, reinforcing the causal link between government directive and physician behavior.

These findings have profound implications for policymakers globally. Firstly, they underscore the crucial role of government directives in shaping professional behavior during periods of uncertainty. During precarious times, evidence-based guidelines are essential to medical professionals' decision-making and prioritizing patient well-being. Secondly, the findings highlight the need for policymakers to consider the potential for unintended consequences and heterogeneous responses among different physician groups. Thirdly, this study emphasizes the importance of continuous monitoring and evaluation of policies to assess their impact on healthcare practices and patient outcomes. Rapid adjustments may be necessary based on evolving scientific evidence and real-world observations. Fourthly, our work can inform policymakers about the need to consider all stakeholders while designing a directive during uncertain times.

From a managerial perspective, this study underscores the importance of effective communication and knowledge dissemination within healthcare organizations. Physicians need access to up-to-date information and clear guidelines to navigate complex situations like pandemics. Hospitals and clinics should foster an environment of continuous learning and adaptation to ensure physicians can effectively respond to evolving health challenges.

Our study is not without limitations. The data we use for our analysis provides physician prescriptions. The paucity of sales data limits our capability to understand the price mechanism involved in this decision-making. We study the change in the prescription of Ivermectin at an extensive margin. Future researchers can study at an intensive margin the effect on skin patients who were ideally supposed to get Ivermectin.

The case of Ivermectin prescriptions in India during the COVID-19 pandemic illustrates how government nudges can catalyze swift changes in professional decision-making, even when clinical evidence is inconclusive. Physicians responded not only to the government's directive but did so in a strategically cautious manner, demonstrating both compliance and risk management. These findings emphasize the double-edged nature of regulatory influence: while timely guidance can mobilize frontline responses during crises, poorly supported directives may also lead to questionable clinical practices. The study concludes that policy design in uncertain environments must account for both intended impacts and behavioral adaptations among professionals. Moreover, it highlights the importance of continuous policy reassessment and clear communication to mitigate unintended consequences in public health interventions.

References

Agarwal, Ritu, Dugas, Michelle, Gao, Guodong Gordon, & Kannan, PK. 2020. Emerging technologies and analytics for a new era of value-centered marketing in healthcare. *Journal of the Academy of Marketing Science*, **48**(1), 9–23.

Agrawal, Shubhangi, Rathi, Sawan, Chatterjee, Chirantan, & Higgins, Matthew J. 2024. *Do Stronger IPR Incentivize Female Participation in Innovation? Evidence from Chinese AI Patents*. Tech. rept. National Bureau of Economic Research.

Ailawadi, Kusum, Chan, Tat, Manchanda, Puneet, & Sudhir, K. 2020. Introduction to the special issue on marketing science and health. *Marketing Science*, **39**(3), 459–464.

Amaldoss, Wilfred, & He, Chuan. 2009. Direct-to-consumer advertising of prescription drugs: A strategic analysis. *Marketing Science*, **28**(3), 472–487.

Angrist, Joshua D, & Pischke, Jörn-Steffen. 2009. *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Barnett, Michael L, Gaye, Marema, Jena, Anupam B, & Mehrotra, Ateev. 2022. Association of County-Level Prescriptions for Hydroxychloroquine and Ivermectin With County-Level Political Voting Patterns in the 2020 US Presidential Election. *JAMA Internal Medicine*, **182**(4), 452–454.

Bodnar, Olivia, Gravelle, Hugh, Gutacker, Nils, & Herr, Annika. 2024. Financial incentives and prescribing behavior in primary care. *Health Economics*, **33**(4), 696–713.

Caly, Leon, Druce, Julian D, Catton, Mike G, Jans, David A, & Wagstaff, Kylie M. 2020. The FDA-approved drug ivermectin inhibits the replication of SARS-CoV-2 in vitro. *Antiviral Research*, **178**, 104787.

Carrieri, Vincenzo, Madio, Leonardo, & Principe, Francesco. 2020. Do-It-Yourself medicine? The impact of light cannabis liberalization on prescription drugs. *Journal of Health Economics*, **74**, 102371.

Chervenak, Frank A, McCullough, Laurence B, & Grünebaum, Amos. 2022. Reversing physician hesitancy to recommend COVID-19 vaccination for pregnant patients. *American Journal of Obstetrics and Gynecology*, **226**(6), 805–812.

Ching, Andrew T, Clark, Robert, Horstmann, Ignatius, & Lim, Hyunwoo. 2016. The effects of publicity on demand: The case of anti-cholesterol drugs. *Marketing Science*, **35**(1), 158–181.

Chintagunta, Pradeep K, Goettler, Ronald L, & Kim, Minki. 2012. New drug diffusion when forward-looking physicians learn from patient feedback and detailing. *Journal of Marketing Research*, **49**(6), 807–821.

Chua, Kao-Ping, Conti, Rena M, & Becker, Nora V. 2022. US Insurer Spending on Ivermectin Prescriptions for COVID-19. *JAMA*.

Dai, Tinglong, & Singh, Shubhranshu. 2020. Conspicuous by its absence: Diagnostic expert testing under uncertainty. *Marketing Science*, **39**(3), 540–563.

Dai, Tinglong, & Singh, Shubhranshu. 2025. EXPRESS: artificial intelligence on call: the physician's decision of whether to use AI in clinical practice. *Journal of Marketing Research*, 00222437251332898.

Davari, Majid, Khorasani, Elahe, & Tigabu, Bereket Molla. 2018. Factors influencing prescribing decisions of physicians: a review. *Ethiopian Journal of Health Sciences*, **28**(6).

de Arruda Castro, Gabriel, & Reich, Gary M. 2024. Anti-Science Populism Versus Brazil's Covid-19 Vaccination Program: A Tale of Two Pandemic Stories. *Journal of Politics in Latin America*, 1866802X241282693.

DellaVigna, Stefano, & Linos, Elizabeth. 2022. RCTs to scale: Comprehensive evidence from two nudge units. *Econometrica*, **90**(1), 81–116.

Fischer, Marc, & Albers, Sönke. 2010. Patient-or physician-oriented marketing: what drives primary demand for prescription drugs? *Journal of Marketing Research*, **47**(1), 103–121.

Fisher, Ronald Aylmer. 1936. Design of experiments. *British Medical Journal*, **1**(3923), 554.

Gaynor, Martin, Ho, Kate, & Town, Robert J. 2015. The industrial organization of health-care markets. *Journal of Economic Literature*, **53**(2), 235–84.

Goli, Ali, Mummalaneni, Simha, & Chintagunta, Pradeep K. 2024. Making a Smooth Exit? Menthol Bans and Cigarette Sales in Massachusetts. *Marketing Science*, **43**(3), 564–589.

Gönül, Füsun F, Carter, Franklin, Petrova, Elina, & Srinivasan, Kannan. 2001. Promotion of prescription drugs and its impact on physicians' choice behavior. *Journal of Marketing*, **65**(3), 79–90.

Gramelspacher, Gregory P, Zhou, Xiao-Hua, Hanna, Mark P, & Tierney, William M. 1997. Preferences of physicians and their patients for end-of-life care. *Journal of General Internal Medicine*, **12**(6), 346–351.

Guo, Tong, Sriram, Srinivasaraghavan, & Manchanda, Puneet. 2020. âLet the sunshine inâ: The impact of industry payment disclosure on physician prescription behavior. *Marketing Science*, **39**(3), 516–539.

Heß, Simon. 2017. Randomization inference with Stata: A guide and software. *The Stata Journal*, **17**(3), 630–651.

Jaikumar, Saravana, Chintagunta, Pradeep K, & Sahay, Arvind. 2024. Do No Harm? Unintended Consequences of Pharmaceutical Price Regulation in India. *Journal of Marketing*, **88**(6), 1–23.

Jayanthy, G, Majumdar, Arnab, Kaloo, Supriya, & Shah, Snehal. 2024. Enhancing patient safety: Leveraging artificial intelligence-powered electronic medical records for effective drug-drug interaction nudge in real-world prescribing practices. *International Journal of Basic & Clinical Pharmacology*, **13**(4), 520–525.

Kerr, Lucy, Baldi, Fernando, Lobo, Raysildo, Assagra, Washington Luiz, Proença, Fernando Carlos, Chamie, Juan J, Hibberd, Jennifer A, Kory, Pierre, Cadegiani, Flavio A, Assagra Sr, Washington Luiz, *et al.* 2022. Regular use of ivermectin as prophylaxis for COVID-19 led up to a 92% reduction in COVID-19 mortality rate in a dose-response manner: results of a prospective observational study of a strictly controlled population of 88,012 subjects. *Cureus*, **14**(8).

Kim, Bokyung. 2021. Must-access prescription drug monitoring programs and the opioid overdose epidemic: the unintended consequences. *Journal of Health Economics*, **75**, 102408.

Kory, Pierre, Meduri, Gianfranco Umberto, Varon, Joseph, Iglesias, Jose, & Marik, Paul E. 2021. Review of the emerging evidence demonstrating the efficacy of ivermectin in the prophylaxis and treatment of COVID-19. *American Journal of Therapeutics*, **28**(3), e299.

Li, Jing, Dow, William H, & Kariv, Shachar. 2017. Social preferences of future physicians. *Proceedings of the National Academy of Sciences*, **114**(48), E10291–E10300.

Lind, Jennifer N, Lovegrove, Maribeth C, Geller, Andrew I, Uyeki, Timothy M, Datta, S Deblina, & Budnitz, Daniel S. 2021. Increase in outpatient ivermectin dispensing in the US during the COVID-19 pandemic: a cross-sectional analysis. *Journal of General Internal Medicine*, **36**(9), 2909–2911.

Moorman, Christine, van Heerde, Harald J, Moreau, C Page, & Palmatier, Robert W. 2024. Marketing in the health care sector: disrupted exchanges and new research directions. *Journal of Marketing*, **88**(1), 1–14.

Munir, Shehryar, Said, Farah, Taj, Umar, & Zafar, Maida. 2022. Digital'nudges' to increase childhood vaccination compliance: Evidence from Pakistan. *arXiv preprint arXiv:2209.06624*.

Nagler, Markus, Piopiunik, Marc, & West, Martin R. 2020. Weak markets, strong teachers: Recession at career start and teacher effectiveness. *Journal of Labor Economics*, **38**(2), 453–500.

Rathi, Manisha, Majumdar, Adrija, & Rathi, Sawan. 2024a. Unraveling Prosumption Behavior for Online Reviews during Environmental Uncertainty: A Stimulus-Response Perspective. *Information Systems Frontiers*, 1–21.

Rathi, Sawan, Majumdar, Adrija, & Chatterjee, Chirantan. 2024b. Did the COVID-19 pandemic propel usage of AI in pharmaceutical innovation? New evidence from patenting data. *Technological Forecasting and Social Change*, **198**, 122940.

Reis, Gilmar, Silva, Eduardo ASM, Silva, Daniela CM, Thabane, Lehana, Milagres, Aline C, Ferreira, Thiago S, Dos Santos, Castilho VQ, Campos, Vitoria HS, Nogueira, Ana MR, de Almeida, Ana PFG, *et al.* 2022. Effect of early treatment with ivermectin among patients with Covid-19. *New England Journal of Medicine*, **386**(18), 1721–1731.

Rosenbaum, Paul R. 2002. Overt bias in observational studies. *Pages 71–104 of: Observational Studies*. Springer.

Rothstein, Mark A. 2017. Ethical responsibilities of physicians in the opioid crisis. *The Journal of Law, Medicine & Ethics*, **45**(4), 682–687.

Shao, Xiaodan, Choudhary, Vivek, Majumdar, Arnab, & Pithawala, Burhanuddin. 2023. To Err is Human: A Field Experiment in Nudging Doctors. *Available at SSRN*.

Shapiro, Bradley T. 2018. Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants. *Journal of Political Economy*, **126**(1), 381–437.

Shapiro, Bradley T. 2022. Promoting wellness or waste? evidence from antidepressant advertising. *American Economic Journal: Microeconomics*, **14**(2), 439–477.

Temple, Courtney, Hoang, Ruby, & Hendrickson, Robert G. 2021. Toxic effects from ivermectin use associated with prevention and treatment of COVID-19. *New England Journal of Medicine*, **385**(23), 2197–2198.

Ventola, C Lee. 2015. The antibiotic resistance crisis: part 1: causes and threats. *Pharmacy and Therapeutics*, **40**(4), 277.

Figures

Figure 1: **Word Cloud of Patient Complaints**. This figure shows the change in the word cloud of patient complaints from pre-COVID to post-COVID when the same drug (Ivermectin) was prescribed. The top panel shows keywords corresponding to patient complaints when Ivermectin was prescribed before COVID-19, and the bottom panel shows the same during the COVID-19 period.

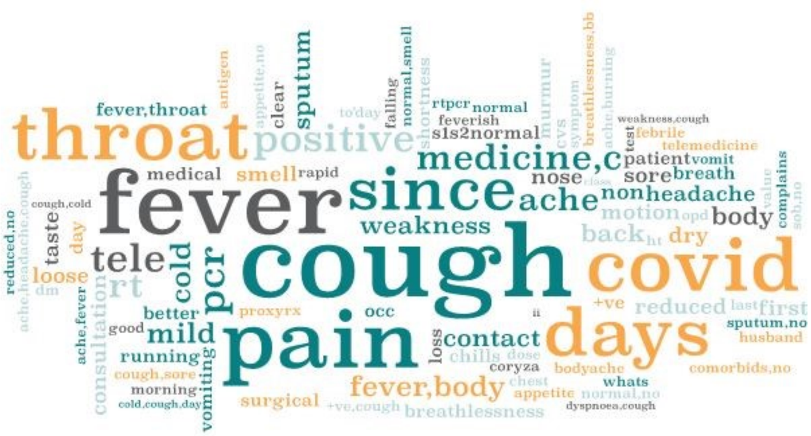


Figure 2: **Timeline of Events.** This figure unfolds the timeline of the important publications, reports, and government directives that followed during the first and second wave of COVID-19 in India.

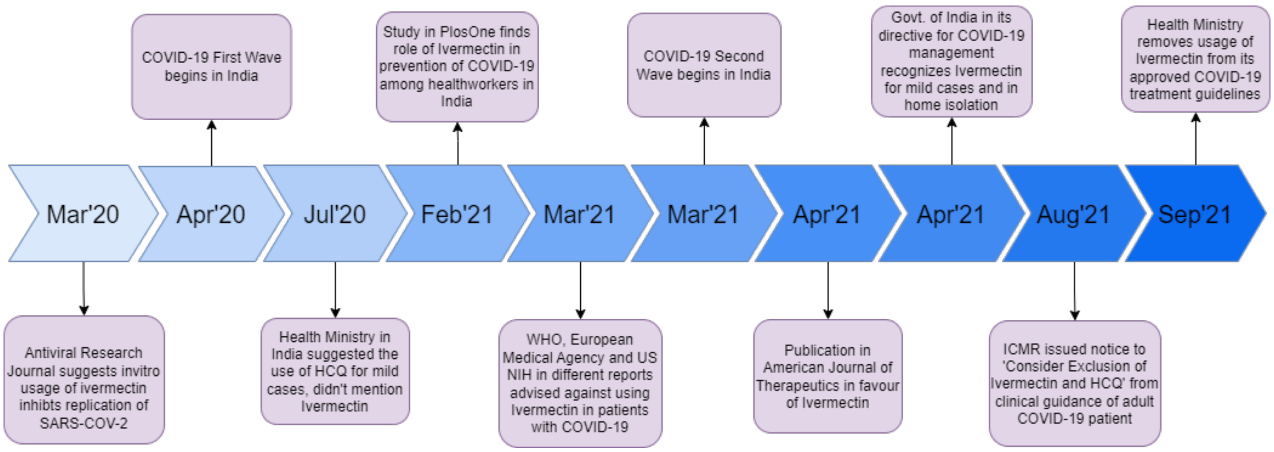


Figure 3: **Event Study Plot (Baseline Results).** The point estimates are interaction coefficients from December 2020 to June 2021 (November is the base year). The vertical line corresponding to each point estimate indicates the 95% confidence interval. The dashed-dotted reference line indicates the beginning of the second wave of COVID-19 in India. The horizontal red line at 0 indicates no significant difference between the treated and control groups.

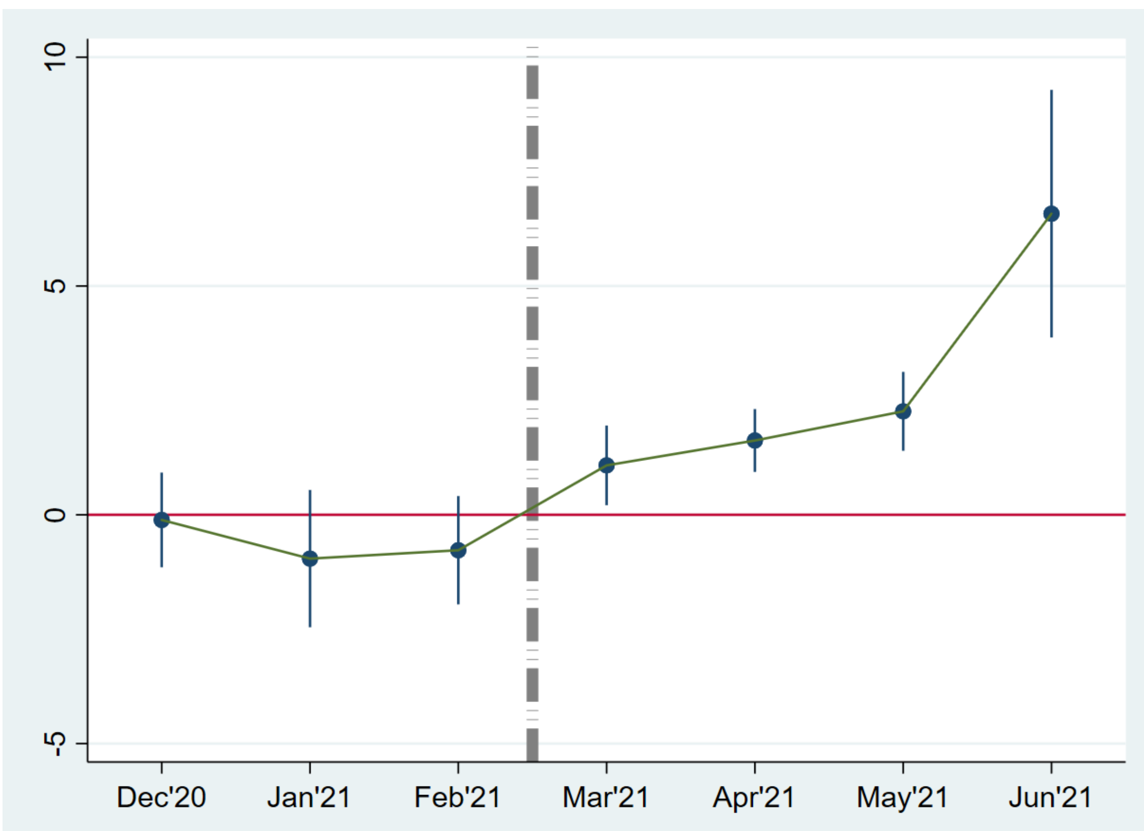


Figure 4: **Higher Ivermectin Prescription to Young Persons.** This figure shows month-wise Ivermectin prescriptions to individuals in different age brackets over 2020 and 2021. We can see that most of the prescriptions during the second wave of COVID-19 (March 2021 to June 2021) were for young people between 30 and 50 years of age.

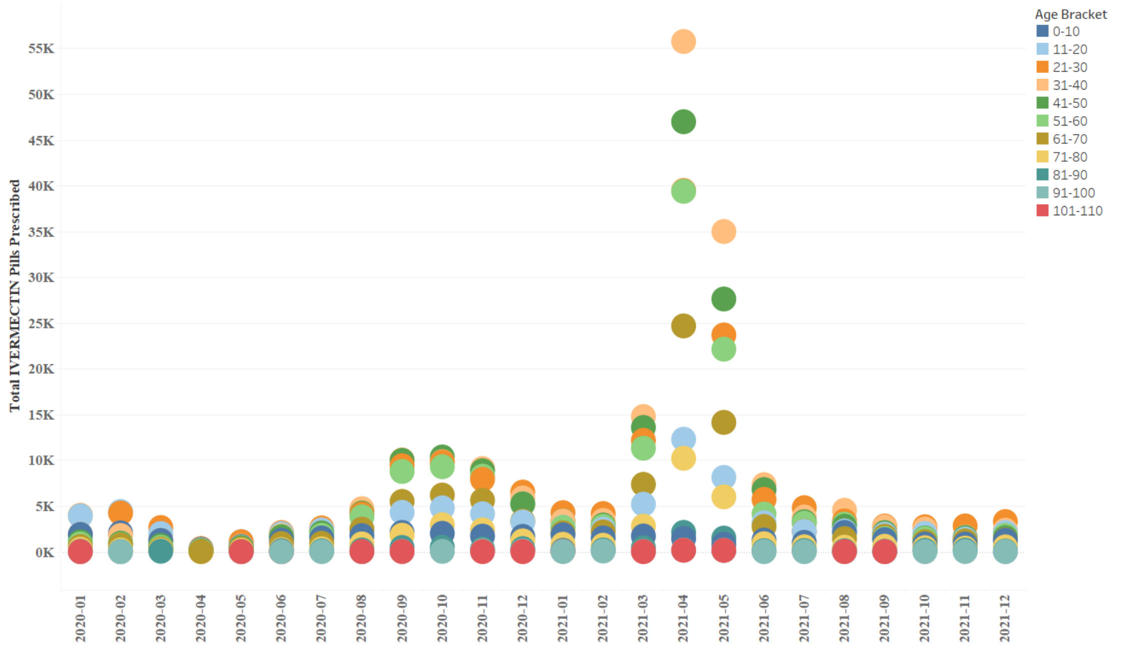


Figure 5: **Ivermectin Prescription in 2019 led by Dermatologists.** This figure shows that in 2019 which is a year before COVID-19 the prescription of Ivermectin was mostly led by Dermatologists.

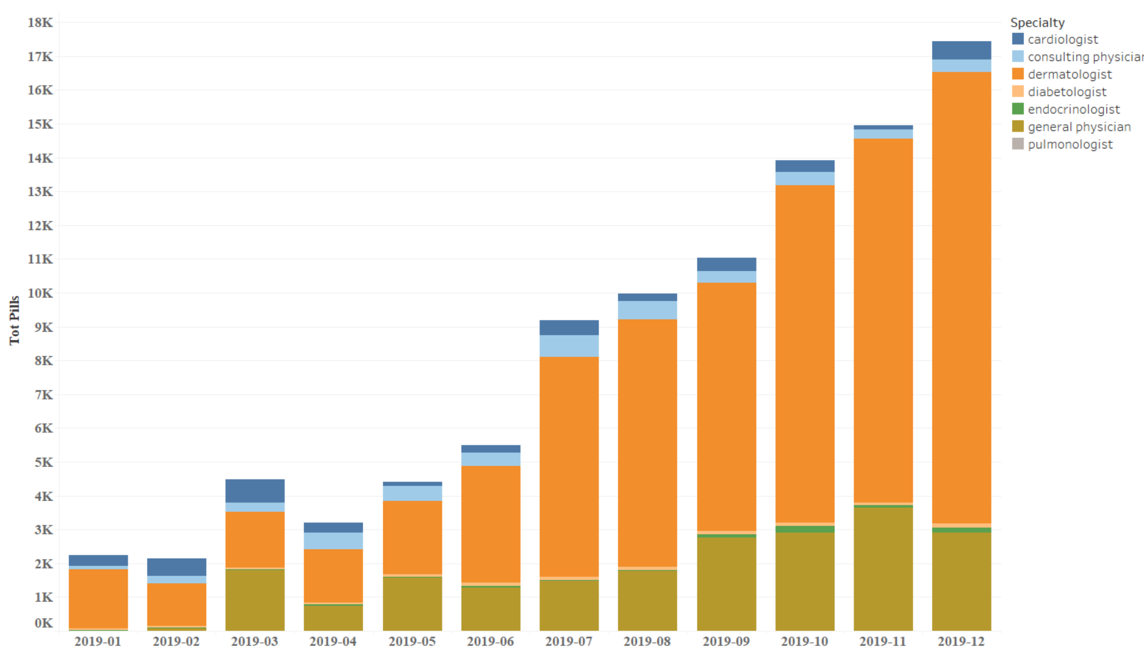


Figure 6: **Ivermectin Prescription in 2020-21 led by consulting and general Physicians.** This figure shows the number of Ivermectin pills prescribed by consulting physicians, general physicians and dermatologists. Importantly, we see that the number of prescriptions by dermatologists is unperturbed to COVID-19 second wave that starts from March 2021.

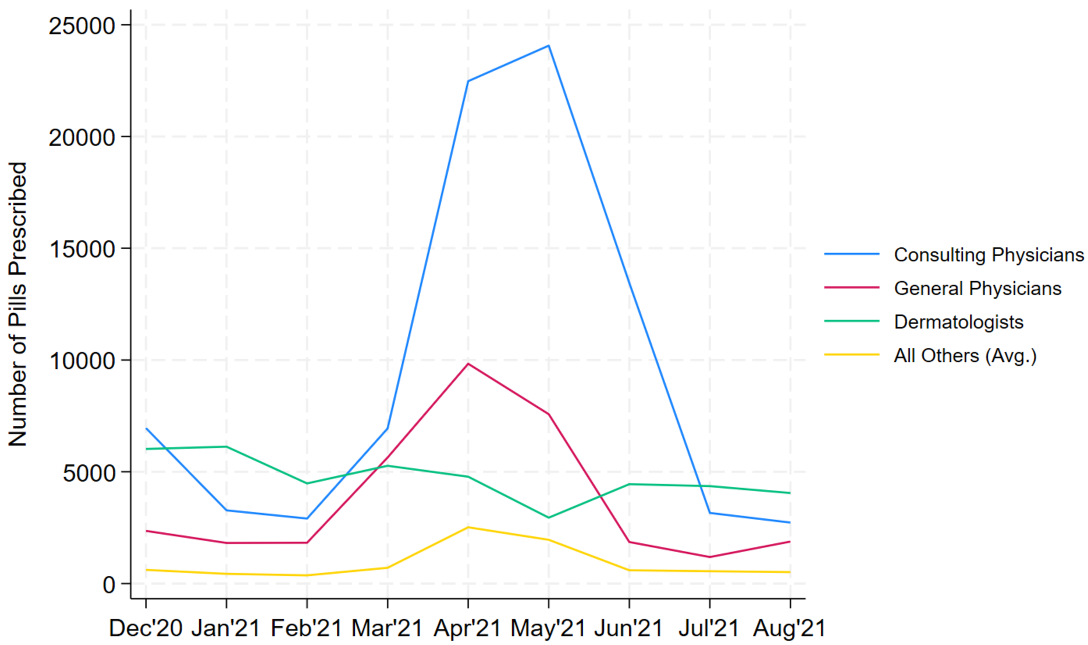
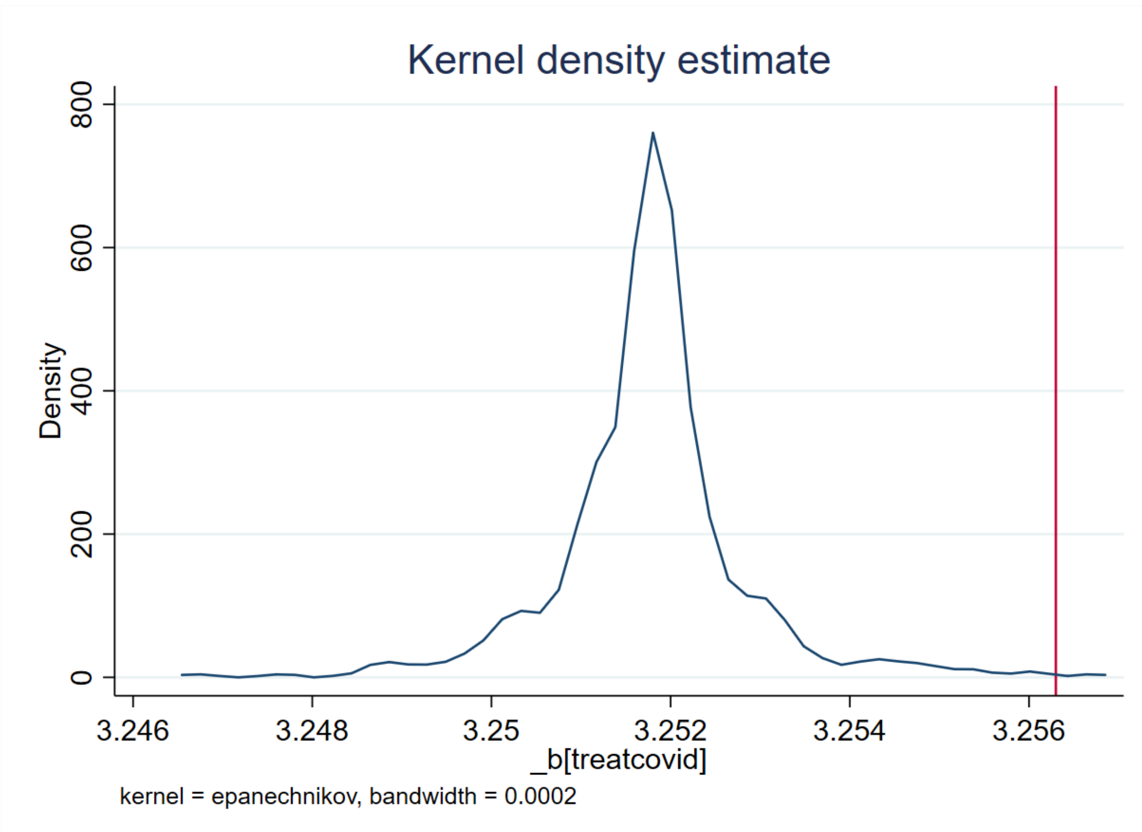


Figure 7: **Randomized Inference Test.** Based on equation 9, we generate a kernel density plot of interaction coefficients obtained after 500 randomization. We see that the interaction coefficient from our baseline specification (column 1 in table 4) shown by the vertical red line in the figure is significantly different from the coefficients obtained after randomization.



Tables

Table 1: Variable Description

Dependent Variables	Definition and Construction
Number of Pills Prescribed	Calculated as Number of Prescriptions x Dosage Frequency x Duration
Prescriptions	Number of Prescriptions by the doctor with a particular specialization to an individual of a particular age and gender belonging to a particular state in a particular month
Dosage Frequency	Number of times in a day the medicine is supposed to be taken by the patient
Independent Variables	**Definition and Construction**
Physicians	Coded as 1 if the specialization of the doctor is Consulting Physician or General Physician, 0 otherwise
Young People	Coded as 1 if the age of the patient is below 60, 0 otherwise
COVID-19 Second Wave	Coded as 1 if the month in which patient took prescription lies from March 2021 to June 2021, 0 otherwise
COVID-19 First Wave	Coded as 1 if the month in which patient took prescription lies from April 2020 to July 2020, 0 otherwise

Table 2: Summary Statistics

Variable	Obs.	Mean	Std.Dev.	Min	Max
Number of Pills Prescribed	30180	9.098	13.573	2.000	672.000
Prescriptions	30180	1.567	1.014	1.000	15.000
Dosage Frequency	30180	1.178	0.342	1.000	3.000
Physicians	30180	0.393	0.488	0.000	1.000
COVID-19 Second Wave	30180	0.667	0.471	0.000	1.000
Gender (Male)	30180	0.544	0.498	0.000	1.000
Age	30180	43.652	19.446	0.000	104.000
Young People (Age $<$ 60)	30180	0.761	0.426	0.000	1.000
Younger People (Age $<$ 45)	30180	0.529	0.499	0.000	1.000

Notes: The table shows the number of observations, mean, standard deviation, minimum value, and maximum value.

Table 3: DID Summmary Statistics

Number of Pills Prescribed	Pre	Post	Difference
Consulting/ General Physician	7.946	11.618	First Difference = 3.672 (t = 9.574, p = 0.000)
Rest Specialist	8.206	8.324	Second Difference = 0.118 (t = 1.028, p = 0.304)
			Difference-in-Differences = 3.554 (t = 10.55, p = 0.000)

Notes: The table represents the initial summary statistics in the difference-in-differences framework. We show mean values of our dependent variable pre and post-COVID-19 second wave and calculate first and second difference values along with respective t-stat and p-value. The post-period indicates months from March 2021 to June 2021, and the pre-period includes months from November 2020 to February 2021. For both the variables, we find a difference-in-differences (first difference - second difference) value to be positive and significant.

Table 4: Increase in Ivermectin Pills Prescribed by Physicians during Second Wave

DV: Number of Pills Prescribed	(1)	(2)	(3)	Log Pills
Physicians x COVID-19 Second Wave	3.516***	3.051***	2.613***	0.169***
	[0.330]	[0.327]	[0.319]	[0.016]
COVID-19 Second Wave	0.105	2.025***		
	[0.135]	[0.587]		
Physicians	-0.264			
	[0.247]			
Month Dummies	No	Yes	Yes	Yes
State Dummies	No	Yes	Yes	Yes
Gender Dummies	No	Yes	Yes	Yes
Age Dummies	No	Yes	Yes	Yes
Doc.Speciality Dummies	No	Yes	Yes	Yes
State-Time Dummies	No	No	Yes	Yes
State-Speciality Dummies	No	No	Yes	Yes
State-Gender Dummies	No	No	Yes	Yes
Gender-Speciality Dummies	No	No	Yes	Yes
Age-Speciality Dummies	No	No	Yes	Yes
Observations	30,180	30,180	30,180	30,180
Adjusted R-squared	0.013	0.095	0.304	0.373

Notes: The dependent variable in all columns is the number of pills prescribed. Across model specifications, we see that the interaction term is positive and statistically significant. Thus, the number of Ivermectin pills prescribed by consulting and general physicians significantly increased during the COVID-19 second wave. The time horizon is November 2020 to June 2021. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 5: Increase in Ivermectin Prescription and Dosage Frequency during Second Wave

	(1) Dose Frequency	(2) Dose Frequency	(3) Prescription	(4) Prescription
Physicians x COVID-19 Second Wave	0.025***	0.024***	0.149***	0.331***
	[0.008]	[0.007]	[0.021]	[0.021]
COVID-19 Second Wave	0.002		0.155***	
	[0.008]		[0.016]	
Physicians	-0.034***		0.323***	
	[0.005]		[0.013]	
Month Dummies	No	Yes	No	Yes
State Dummies	No	Yes	No	Yes
Gender Dummies	No	Yes	No	Yes
Age Dummies	No	Yes	No	Yes
Doc.Speciality Dummies	No	Yes	No	Yes
State-Time Dummies	No	Yes	No	Yes
State-Speciality Dummies	No	Yes	No	Yes
State-Gender Dummies	No	Yes	No	Yes
Gender-Speciality Dummies	No	Yes	No	Yes
Age-Speciality Dummies	No	Yes	No	Yes
Observations	0.003	0.500	0.071	0.285
Adjusted R-squared	30,180	30,180	30,180	30,180

Notes: The dependent variable in column (1) and column (2) is dose frequency, and in column (3) and column (4) is the number of prescriptions. Across model specifications, we see that the interaction term is positive and statistically significant. Thus, both dosage frequency and number of prescriptions by consulting and general physicians significantly increased during the COVID-19 second wave. The time horizon is November 2020 to June 2021. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 6: Increase in Number of Prescriptions to Youngsters by Physicians

DV: Number of Pills Prescribed	(1)	(2)	(3)	(4)
	Young People Age < 60			Age < 45
Young People x COVID-19 Second Wave	0.841***	0.841***	1.805***	0.678***
	[0.281]	[0.282]	[0.288]	[0.273]
COVID-19 Second Wave	0.888***	2.602***		
	[0.218]	[0.670]		
Young People	1.074***			
	[0.214]			
Month Dummies	No	Yes	Yes	Yes
State Dummies	No	Yes	Yes	Yes
Gender Dummies	No	Yes	Yes	Yes
Age Dummies	No	Yes	Yes	Yes
Doc.Speciality Dummies	No	Yes	Yes	Yes
State-Time Dummies	No	No	Yes	Yes
State-Speciality Dummies	No	No	Yes	Yes
State-Gender Dummies	No	No	Yes	Yes
Gender-Speciality Dummies	No	No	Yes	Yes
Age-Speciality Dummies	No	No	Yes	Yes
Observations	30,180	30,180	30,180	30,180
Adjusted R-squared	0.012	0.093	0.303	0.303

Notes: The dependent variable in all columns is the number of pills prescribed. Across model specifications, we see that the interaction term is positive and statistically significant. Thus, the number of Ivermectin pills prescribed by physicians significantly increased for young people (both below 45 and 60 years of age) during the COVID-19 second wave. The time horizon is November 2020 to June 2021. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 7: No Effect on Ivermectin Prescription in COVID-19 First Wave

DV: Number of Pills Prescribed	(1)	(2)	(3)	(4)
Physicians x COVID-19 First Wave	-0.771	-3.549*		
	[1.070]	[1.986]		
Young People x COVID-19 First Wave			0.924	-0.585
			[0.915]	[0.913]
COVID-19 First Wave	-4.315***		-5.838***	
	[0.538]		[0.933]	
Physicians	-2.250**			
	[1.032]			
Young People			0.728	
			[0.840]	
Month Dummies	No	Yes	No	Yes
State Dummies	No	Yes	No	Yes
Gender Dummies	No	Yes	No	Yes
Age Dummies	No	Yes	No	Yes
Doc.Speciality Dummies	No	Yes	No	Yes
State-Time Dummies	No	Yes	No	Yes
State-Speciality Dummies	No	Yes	No	Yes
State-Gender Dummies	No	Yes	No	Yes
Gender-Speciality Dummies	No	Yes	No	Yes
Age-Speciality Dummies	No	Yes	No	Yes
Observations	5,454	5,454	5,454	5,454
Adjusted R-squared	0.056	0.320	0.045	0.318

Notes: The dependent variable in all columns is the number of pills prescribed. Across model specifications, the interaction term is either insignificant or negative. Thus, we find no change in physician prescription during India's first wave of COVID-19. The time horizon is January 2020 to July 2020. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 8: Ivermectin prescribed for COVID related complaints during second wave

DV: Topic 1 & 2	(1)	(2)	(3)
Physicians x COVID-19 Second Wave	0.001	0.001*	0.002***
	[0.001]	[0.001]	[0.001]
COVID-19 Second Wave	-0.003***	-0.002***	
	[0.001]	[0.001]	
Physicians	-0.004***		
	[0.001]		
Month Dummies	No	Yes	Yes
State Dummies	No	Yes	Yes
Gender Dummies	No	Yes	Yes
Age Dummies	No	Yes	Yes
Doc.Speciality Dummies	No	Yes	Yes
State-Time Dummies	No	No	Yes
State-Speciality Dummies	No	No	Yes
State-Gender Dummies	No	No	Yes
Gender-Speciality Dummies	No	No	Yes
Age-Speciality Dummies	No	No	Yes
Observations	19,674	19,674	19,674
Adjusted R-squared	0.017	0.081	0.106

Notes: The dependent variable in all columns is the probability of complaint keywords being related to COVID-19 (Topic 1 and 2). Across model specifications, the interaction term is positive. Thus, we find an increase in the prescription of Ivermectin by consulting and general physicians when the patient's complaint is related to COVID-19. The time horizon is November 2020 to June 2021. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 9: No Spillovers with Dermatologist

DV: Number of Pills Prescribed	(1)	(2)	(3)
Physicians x COVID-19 Second Wave	2.256***	2.694***	
	[0.501]	[0.341]	
Dermatologists x COVID-19 Second Wave			-0.588
			[0.392]
Month Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Gender Dummies	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes
Doc.Speciality Dummies	Yes	Yes	Yes
State-Time Dummies	Yes	Yes	Yes
State-Speciality Dummies	Yes	Yes	Yes
State-Gender Dummies	Yes	Yes	Yes
Gender-Speciality Dummies	Yes	Yes	Yes
Age-Speciality Dummies	Yes	Yes	Yes
Observations	15,722	26,308	18,322
Adjusted R-squared	0.383	0.316	0.232

Notes: The dependent variable in all columns is the total number of pills prescribed. In column (1) we do a sub-sample analysis with only dermatogists as control group, in column (2) we keep all specialities in control group except dermatologist and in column (3) we keep dermatalogists a treatment group and all others as control. The time horizon is November 2020 to June 2021. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***,' '**,' and'*' indicate significance at the 1%, 5%, and 10%, respectively.

Table 10: Ivermectin prescription falls as the government withdraws its directive

	(1) Dose Frequency	(2) Prescriptions	(3) Number of Pills
Physicians	-0.049***	0.010	-3.676***
	[0.008]	[0.015]	[0.351]
Constant	1.125***	1.215***	10.811***
	[0.005]	[0.007]	[0.211]
Month Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Gender Dummies	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes
State-Time Dummies	Yes	Yes	Yes
State-Gender Dummies	Yes	Yes	Yes
Observations	7,712	7,712	7,712
Adjusted R-squared	0.194	0.078	0.079

Notes: The dependent variable in column (1) is dose frequency, column (2) is Prescription count, and column (3) is the total number of pills prescribed. Across model specifications, the interaction term is either negative or statistically insignificant. Thus, we find that the prescription of Ivermectin by consulting and general physicians has stopped or reduced as the government withdraws its directive in favor of Ivermectin. The time horizon is August 2021 to December 2021. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Appendix

Figure A1: **COVID-19 cases in India**. The figure plots the variation of daily new COVID-19 cases in India during the first two waves.

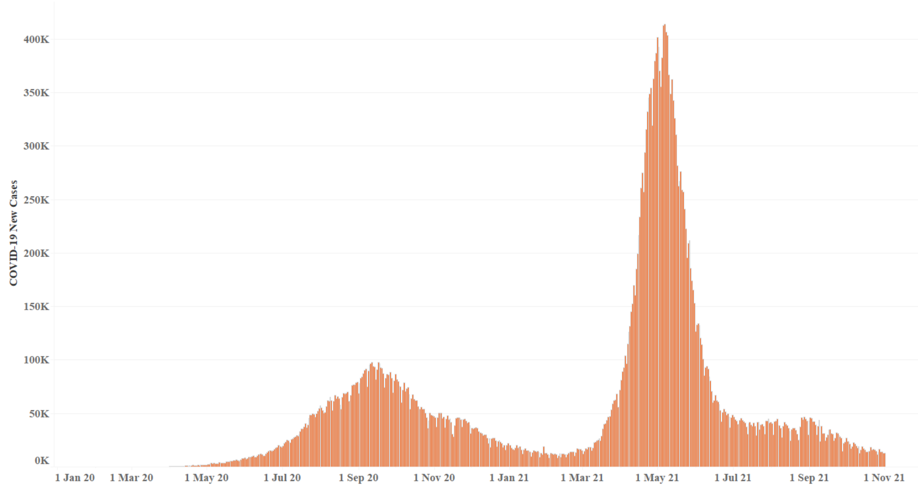
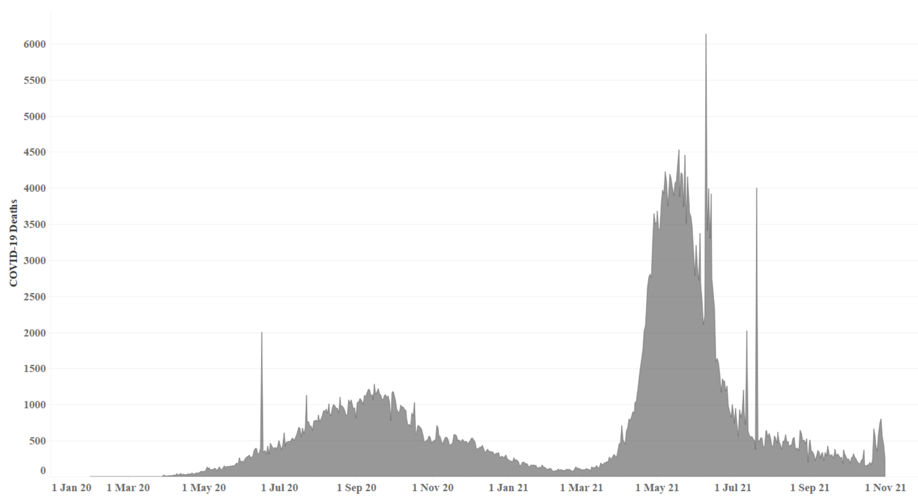


Figure A2: **COVID-19 Deaths in India**. The figure plots the variation of daily new COVID-19 deaths in India during the first two waves.



Online Appendix

Figure B1: **Google Search Trend of Ivermectin**. The figure shows how the trend of the search for the word "Ivermectin" changes in different countries.

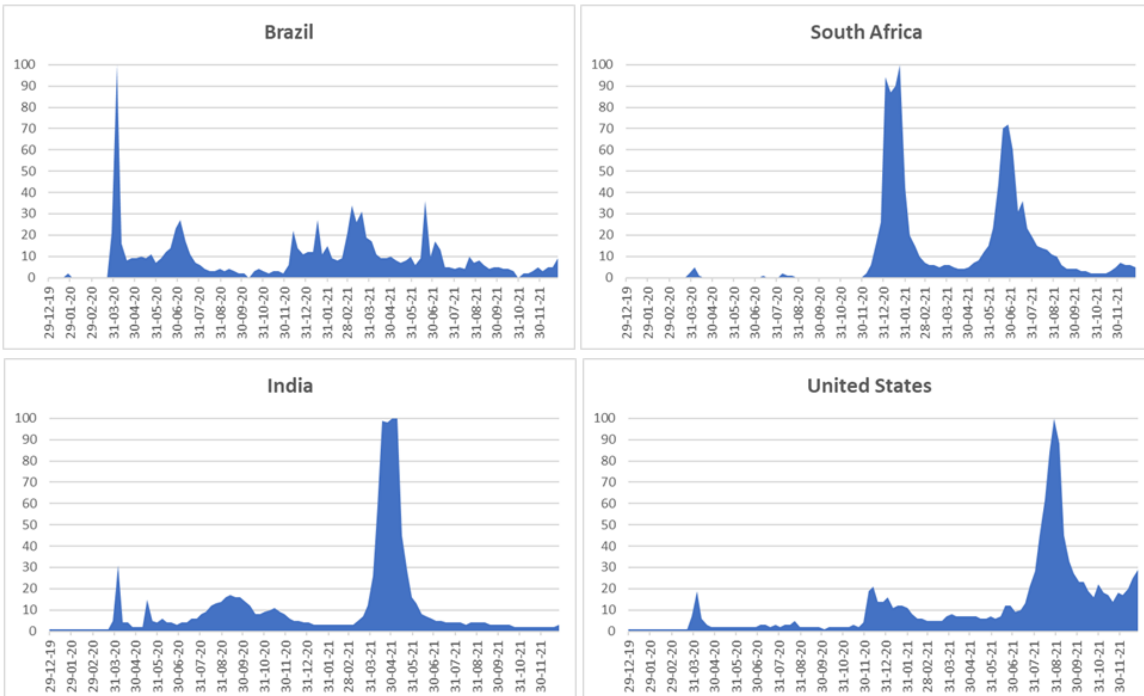


Figure B2: **Event Study Plot (Young People Prescription)**. The point estimates are interaction coefficients from December 2020 to June 2021 (November is the base year). The vertical line corresponding to each point estimate indicates the 95% confidence interval. The vertical red reference line indicates the beginning of the second wave of COVID-19 in India. The horizontal red line at 0 indicates no significant difference between the treated and control groups.

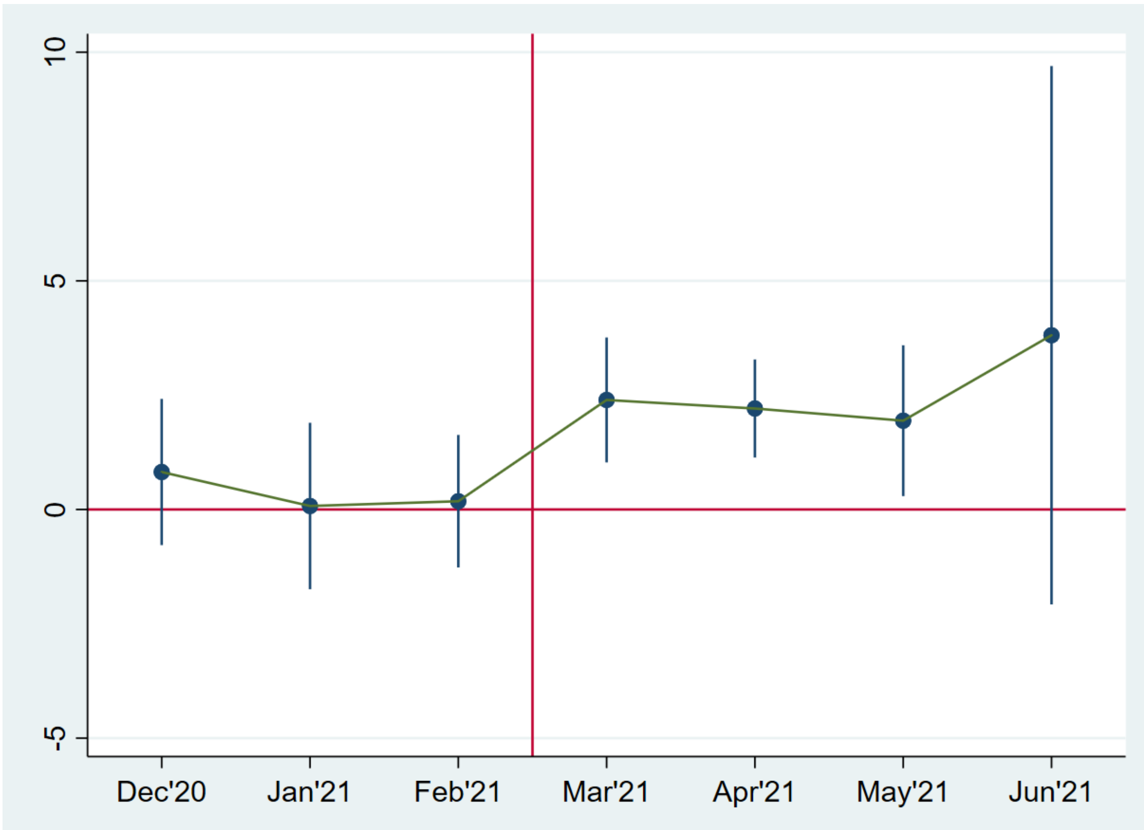
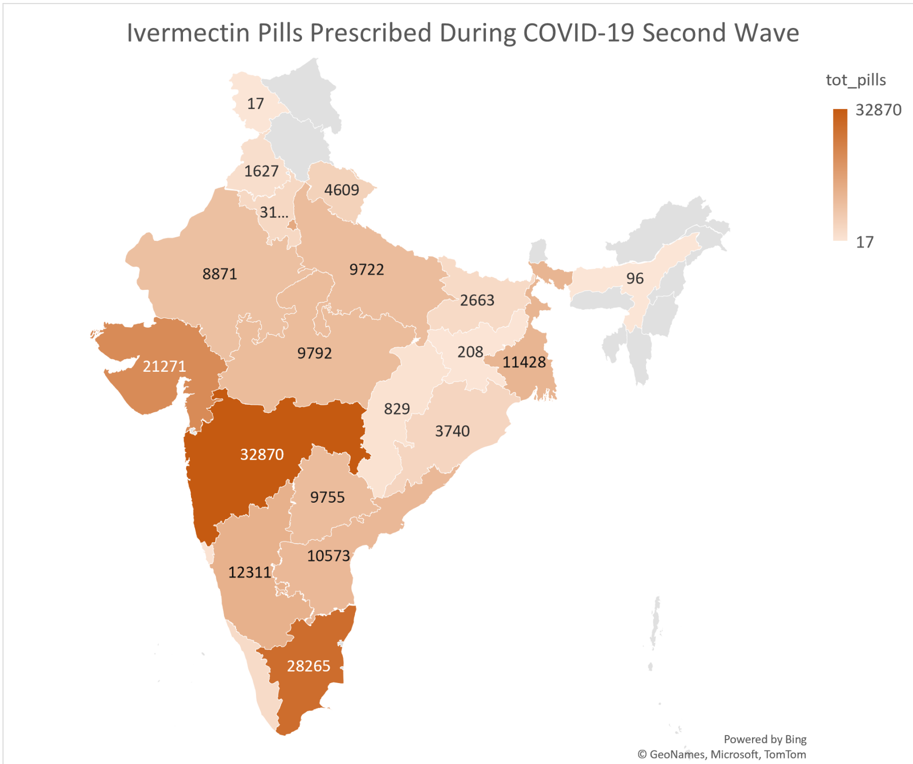


Figure B3: **Ivermectin Prescription Vs. COVID-19 deaths**. The map on the top shows the number of Ivermectin pills prescribed during the second wave of COVID-19 in India. The bottom map populates the number of COVID-19 deaths during the same time. The purpose of this figure is to show that Ivermectin had no impact in controlling COVID-19 in India.



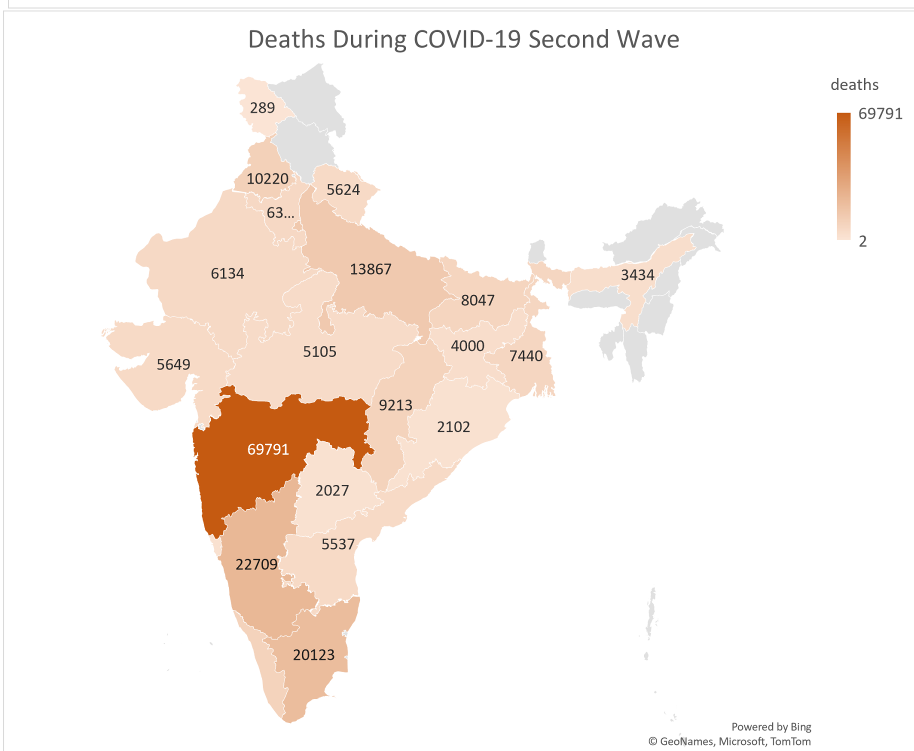


Table B1: Topic Modelling: Keywords

Topic Number	Prominent Keywords
Topic 1	cough, fever, sputum, throat, cold, weak, body pain
Topic 2	covid, positive, rt-pcr, chest, breath, vaccine, symptomatic
Topic 3	itch, lesion, feel, rash, limb, consultation, body, appetit
Topic 4	sore, loose, symptom, motion, back, home, walk, low
Topic 5	burn, vomit, joint, nose, irritation, fever, pain, abdomin

Notes: Table shows top keywords of all topics obtained after LDA topic modeling. Highlighted in blue is the topic that represents keywords related to the COVID-19 pandemic.

Table B2: Randomized Inference Test

Number of Pills Prescribed (T obs)	c	N	p = c/N	SE(p)	95% confidence interval
3.5162	0	500	**0.000**	0.000	0 - 0.0073

Notes: This table presents results from randomization inference (RI) tests of DID model shown equation 9. Coefficient of the interaction term T(obs) is our test statistic as seen in column (1) of table 4. We obtain the distribution of the test statistic under the null hypothesis that the there was no change in number of ivermectin pills prescribed during COVID-19 second wave and use 500 re-randomizations. The p-value of the test statistic is shown in bold font in column 4 of the table. We conducted RI tests using the "ritest" command in Stata developed by Heß (2017).

Table B3: No Impact of Ivermectin in Reducing COVID-19 Cases or Deaths

	(1) Cases	(2) Cases	(3) Deaths	(4) Deaths
Number of Pills Prescribed	76.293***	64.125***	0.959***	0.531***
	[14.044]	[16.501]	[0.192]	[0.152]
Constant	21,158.899	-93,564.188*	321.998**	-1,601.619**
	[17,319.984]	[47,545.758]	[162.767]	[731.520]
Month Dummies	No	Yes	No	Yes
State Dummies	No	Yes	No	Yes
Observations	168	168	168	168
R-squared	0.481	0.756	0.346	0.636

Notes: The dependent variable in columns (1) and (2) is COVID-19 cases, and in columns (3) and (4) is COVID-19 deaths. To see if Ivermectin had an impact on reducing COVID-19 cases or deaths, we collapse the data at the state-month level. The time horizon is March 2021 to December 2021. Robust standard errors are presented in the parentheses.'***','**','*' indicate significance at the 1%, 5%, and 10% respectively.

Table B4: Robustness: Results Hold at Speciality-Location-Time level

	(1) Dose Frequency	(2) Prescriptions	(3) Number of Pills
Physicians x COVID-19 Second Wave	21.191***	52.067***	388.953***
	[4.724]	[9.524]	[92.144]
Month Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Doc.Speciality Dummies	Yes	Yes	Yes
State-Time Dummies	Yes	Yes	Yes
State-Speciality Dummies	Yes	Yes	Yes
Observations	955	955	955
Adjusted R-squared	0.757	0.624	0.510

Notes: The dependent variable in column (1) is dose frequency, column (2) is prescription count, and column (3) is the total number of pills prescribed. Across model specifications, we see that the interaction term is positive and statistically significant. Thus, results hold when we collapse the data at the specialty-location-time level. The time horizon is November 2020 to June 2021. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***,' '**,' and'*' indicate significance at the 1%, 5%, and 10%, respectively.

Table B5: Robustness: Results Hold with Alternative Control Group

	(1) Dose Frequency	(2) Prescriptions	(3) Number of Pills
Physicians x COVID-19 Second Wave	0.029***	0.319***	2.634***
	[0.007]	[0.022]	[0.327]
Month Dummies	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Gender Dummies	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes
Doc.Speciality Dummies	Yes	Yes	Yes
State-Time Dummies	Yes	Yes	Yes
State-Speciality Dummies	Yes	Yes	Yes
State-Gender Dummies	Yes	Yes	Yes
Gender-Speciality Dummies	Yes	Yes	Yes
Age-Speciality Dummies	Yes	Yes	Yes
Observations	27,639	27,639	27,639
Adjusted R-squared	0.311	0.293	0.456

Notes: We create an alternate control group that comprises the top 5 specialists - cardiologists, dermatologists, diabetologists, endocrinologists, and pulmonologists. The dependent variable in column (1) is dose frequency, column (2) is Prescription count, and column (3) is the total number of pills prescribed. Across model specifications, we see that the interaction term is positive and statistically significant. Thus all our results hold even with a changed control group. The time horizon is November 2020 to June 2021. The constant term is included but not reported. Robust standard errors are presented in the parenthesis.'***,' '**,' and'*' indicate significance at the 1%, 5%, and 10%, respectively.