Stockpiling medicines at the onset of the COVID-19 pandemic: an empirical analysis of national prescription drug sales and prices

Stockpiling Medicines at the Onset of the COVID-19 Pandemic: An Empirical Analysis of National Prescription Drug Sales and Prices

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Hospitals with Coronavirus disease (COVID-19) demand surges at the onset of the pandemic report medication shortages, a worrisome phenomenon as inadequate medication supplies negatively affect patient outcomes. The popular press implicates a lack of raw ingredients and spikes in purchases but rigorous research is needed to more accurately identify shortage causes. We leverage a quasi-experimental design on IQVIA's National Sales Perspectives™ data from 2018-2020 with a focus on medicines related to U.S. hospital-based COVID-19 treatment and a set of control medicines not used for COVID-19. We contribute to supply chain theory by empirically demonstrating that stockpiling among U.S. medical providers in the early phase of the pandemic accounts for the shortages. The buyers' behavior results in concentration of the sales volume of COVID-19 medicines in the first two months of the pandemic. After these first two months, the sales volume of drugs for COVID-19 treatment decreases significantly despite a nationwide increase in COVID-19-related hospitalizations. An implication for manufacturers is that orders due to stockpiling by downstream buyers early on in a pandemic period should be discounted when predicting future demand. We also investigate another potential cause: expected price increases in the future. Counter to concerns that drug manufacturers would engage in price gouging behavior, we find no evidence of price inflation for these drugs. Our results are robust to numerous sensitivity checks and have implications for manufacturers, hospitals, and policymakers that may improve medicine supply resiliency against future threats.

Key words: stockpiling, drug shortages, price, COVID-19, difference-in-differences

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1. Introduction

SARS-COV-2 virus is responsible for over 3 million hospitalizations as of October 2021 (CDC 2021). Patients hospitalized with COVID-19 can be successfully treated with prescription drugs that are part of standard treatment guidelines (NIH 2020). Unfortunately, in the early days of the pandemic, hospitals with a surge of COVID-19 patients reported shortages of COVID-19 related medicines (Choo and Rajkumar 2020). For example, in March and April of 2020, New York was one of the first states with COVID-19 patients (see Figure 1). Its hospitals struggled to secure enough drugs (Rowland and Slater 2020, Premier Inc. 2020), personal protective equipment and other needed supplies required for COVID-19 patients (Ranney et al. 2020, U.S. International Trade Commission 2020). Research to understand how to mitigate medical product shortages at the onset of a pandemic is of paramount importance because shortages can stymie healthcare delivery (Shumsky et al. 2021), increase costs (Kaakeh et al. 2011, Fox et al. 2014) and adversely affect patient outcomes (Fox et al. 2014, Tucker 2016).

Medical product shortages stem from both supply and demand-side factors. On the supply side, pandemic-related shortages of masks and other needed supplies were first attributed to supply shortfalls due to disrupted labor, reduction in exports from countries that manufacture the products, and quality problems (Ranney et al. 2020). Supply shortages also plagued prescription drugs. The pandemic shuttered factories in China and Italy that supply drugs to the U.S. (Conti and Berndt 2020, Schondelmeyer et al. 2020). International export bans further restricted medication imports into the U.S. For example, the United Kingdom banned the export of 82 drugs, and India restricted the export of 26 active pharmaceutical ingredients and finished drug products (PTI 2020, Schondelmeyer et al. 2020, Wallace 2020). On the demand side, stockpiling and panic buying were reported to exacerbate shortages of personal protective equipment (WHO 2020). The popular press attributes the New York shortages of COVID-19 related drugs to hospitals in regions not yet hit by COVID-19 stocking up on essential medicines (Gibney and Zipp 2020, Shuman et al. 2020).

Stockpiling is defined as buying larger quantities of products than needed at a given point in time or purchasing products in advance of what is typically used (Blattberg and Neslin 1990, Mela et al. 1998). Consumers stockpile after publicly announced temporary price discounts (Blattberg et al. 1981, Blattberg and Neslin 1990, Lee et al. 1997b, Mela et al. 1998, Hendel and Nevo 2006). Scholars have also documented stockpiling by companies in anticipation of supply chain interruptions due to unexpected demand surges, transportation bottlenecks, labor strikes, natural disasters (Sterman and Dogan 2015), and upstream inventory stockouts (Bray et al. 2019).

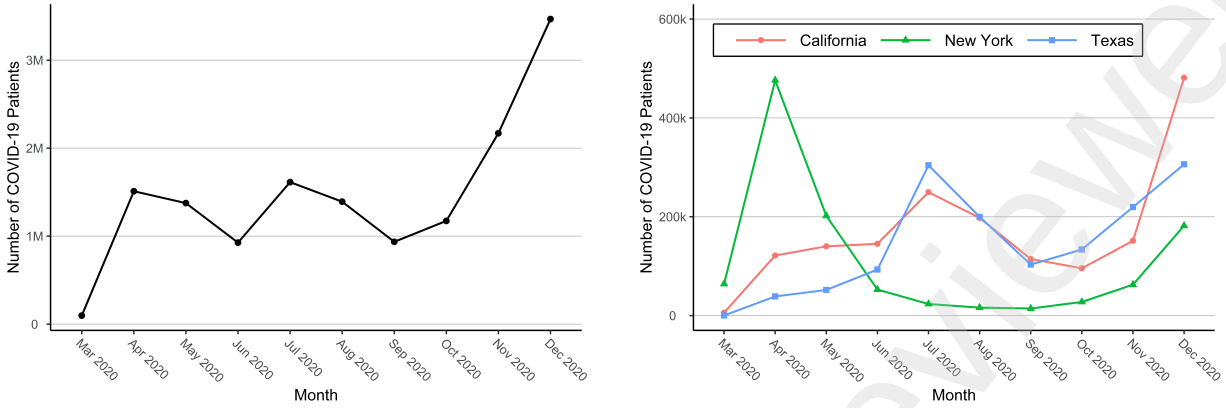
The onset of the COVID-19 pandemic may have engendered stockpiling of prescription drugs by U.S. medical providers. Unique supply chain characteristics of healthcare delivery make it

difficult to respond to unexpected changes in demand for medications (FDA 2019, The White House 2021). Prescription drug manufacturing requires significant upfront costs (Berndt et al. 2017, Yurukoglu et al. 2017). In addition, to sell prescription drugs in the U.S., manufacturers must comply with strict federal regulations for safety and efficacy at the time drugs are approved and subsequently produce drugs in accordance with Current Good Manufacturing Practices (Anand et al. 2012, Woodcock and Wosinska 2013, Jia and Zhao 2017, Conti and Berndt 2020). Finally, there is little timely transparency on the supply and demand of prescription drugs (Woodcock and Wosinska 2013, Fox et al. 2014, Gibson and Singh 2018, FDA 2019, Schondelmeyer et al. 2020). These market characteristics may trigger stockpiling behavior by medical providers who perceive potential supply shortfalls that may not be easily resolved. Anticipating stockpiling behavior, prescription drug manufacturers may price gouge by increasing the price of existing supplies significantly over current levels (Beatty et al. 2021, Cabral and Xu 2021).

Despite popular press coverage, scant rigorous research exists on stockpiling and associated behaviors, such as price gouging, in the face of supply interruptions (Sterman and Dogan 2015, Bray et al. 2019), especially for prescription drugs during a pandemic. For example, Catillon et al. (2020) suggest that media coverage on COVID-19-related drugs may trigger stockpiling of those drugs but stops short of testing that hypothesis. Similarly, Romano et al. (2021) analyze the sales of six medicines in community pharmacies in Portugal and show that sales and reported shortages both increased over pre-COVID levels during the early stage of the outbreak, but do not provide causal estimates of the effects. Some authors raise concerns about price gouging of prescription drugs used to treat COVID-19 (Cleary 2020, Mattingly and Hogue 2020), but we are not aware of any work that has empirically examined the market for drugs to detect statistically significant increases in prices associated with the pandemic.

Our paper addresses these gaps by employing quasi-experimental methods to analyze U.S. sales and prices of 114 medicines used in the treatment of COVID-19. The advent of the pandemic might have plausibly altered purchasing behavior for these drugs. More specifically, we empirically examine whether COVID-19 related drugs experienced statistically significant changes in sales volume and price in the early days of the pandemic. We define the cohort of prescription drugs used for hospital-based COVID-19 treatment using the U.S. FDA Essential Medicine List, the national COVID-19 treatment guidelines (NIH 2020), and expert review by one of the authors who is a hospital pharmacist and a national expert on drug shortages. We also create a matching cohort of drugs not used for COVID-19 treatment to control for changes in demand of non-COVID-19 medical care. To test our hypotheses, we utilize IQVIA's national-level data on all U.S. prescription drug sales in the between January 2018 and September 2020 by medical provider type. We focus on drug sales to hospitals and related facilities because the prescription drugs recommended for managing

Figure 1 U.S. Monthly Hospitalized COVID-19 Patients



(a) National level (b) State level

Notes. Panel (a) plots the monthly sum of daily current hospitalized COVID-19 patients at the national level. Panel (b) plots data for three major states – California, New York, and Texas. *Source*: The COVID Tracking Project at *The Atlantic*.

severe COVID-19 patients are largely administered to inpatients (NIH 2020). Consistent with stockpiling behavior, we find that sales increases of COVID-19 related medicines are concentrated in the first two months of the pandemic after which sales decrease significantly despite an uptick in COVID-19 related hospitalizations nationwide. In contrast, monthly sales volume decreases by 14% on average for the control group medications compared to the pre-pandemic time period. Finally, prices of both groups of medications, on average, do not change significantly in the early pandemic period. This result provides evidence that concerns about price increases during a pandemic might not materialize, eliminating one justification for stockpiling. We conduct robustness checks to rule out alternative explanations and find that our results hold.

2. Related Literature and Hypotheses

In this section, we briefly discuss three streams of literature related to our study: (1) stockpiling behavior, (2) the prescription drug market in the U.S., and (3) price changes during unexpected supply challenges.

2.1. Prior Literature on Stockpiling Behavior and Background on the U.S. Prescription Drug Market

Prior literature has shown that buyers stockpile when they anticipate that cumulative orders to the supplier will exceed available capacity (Sterman and Dogan 2015, Bray et al. 2019). Several factors contribute to this phenomenon. First, anxiety, fear, and panic due to uncertainty or previous experience of supply disruptions may induce stockpiling (Sterman and Dogan 2015, Micalizzi et al. 2020). Second, the lack of information sharing among supply chain members could increase customers' tendency to exaggerate their order quantities because buyers become anxious when they

don't know the supplier's capacity or inventory information (Lee et al. 1997a,b). Third, long and unpredictable supplier lead time may constitute stressors that trigger stockpiling (Sterman and Dogan 2015). Lastly, rationing supply among buyers leads to exaggerated orders because buyers compete to gain a more favorable allocation (Lee et al. 1997a, Cachon and Lariviere 1999, Armony and Plambeck 2005, Bray et al. 2019). Surprisingly, experimental research shows that buyers inflate orders even when there is sufficient supply or no competition for limited supply. This happens when buyers underestimate the amount of product in transit from their suppliers (Sterman 1989, Croson and Donohue 2006, Croson et al. 2014), possess stockout aversion (Schweitzer and Cachon 2000), or do not trust their supply chain partners (Croson et al. 2014). These behavioral factors could contribute to stockpiling during supply interruptions as well. Sterman and Dogan (2015) illustrate that stockpiling itself worsens stockpiling behaviors in supply chains by lengthening the lead time and reducing supplier reliability.

Many of these underlying conditions are present in the U.S. prescription drug market. Medical providers may have strong stockout aversion because a lack of medical supplies can delay treatments (Shumsky et al. 2021), negatively affect patient outcomes (Fox et al. 2014, Tucker 2016), and increase provider costs (Kaakeh et al. 2011, Fox et al. 2014). There is also very little information sharing from drug manufacturers to their buyers on the available supply of prescription drugs which could heighten buyers' anxiety during challenging conditions, such as a pandemic (Gibson and Singh 2018, FDA 2019, Gibney and Zipp 2020, Premier Inc. 2020, Thomas 2020). For example, in February 2020, a drug was in short supply because of COVID-19. Despite the potential benefits of doing so, the FDA declined to reveal to the public the drug's name, manufacturer, or where the product and ingredients were made. This angered public health advocates and created fear and panic for buyers (Thomas 2020). During the early phase of the COVID-19 pandemic, there were no national or state-directed policies intending to reduce competition among buyers, and current allocation policies by drug manufacturers and other members of the supply chain did not account for patient demand surges (Gibney and Zipp 2020, The White House 2021).

In addition, the majority of COVID-19 related inpatient drugs are generic. Generic drugs are ones whose patent protection and market exclusivities have expired. Thus, multiple manufacturers should theoretically be able to supply these products. However, previous empirical work suggests that there are limited supplies of many generic drugs (Conti and Berndt 2020). In particular, some generic drugs used in the inpatient setting experience chronic supply disruptions (Fox et al. 2014, FDA 2019, Doroudi et al. 2020, Thomas 2020, The White House 2021). Several factors contribute to these supply disruptions. First, domestic production capacity is inflexible and expensive due to the need for specialized facilities with dedicated, complex production lines (Woodcock and Wosinska 2013, Jia and Zhao 2017, Wang et al. 2021) that meet current Good Manufacturing

Practices (Anand et al. 2012, Woodcock and Wosinska 2013, Jia and Zhao 2017, Conti and Berndt 2020). Second, base ingredients primarily come from overseas suppliers, with many located in China and India (Berndt et al. 2018, FDA 2019, The White House 2021). Aware of the supply chain risk associated with these factors, health officials and prescription drug purchasers worried about potential shortages during the pandemic (Lupkin 2020). These worries may have motivated stockpiling of drugs at the onset of the pandemic. Moreover, the relatively low competitive price of many generic drugs (Jia and Zhao 2017, Ball et al. 2018, FDA 2019, Wang et al. 2021) might contribute to stockpiling because of low overage costs. Based on these supply chain challenges, we hypothesize the following:

HYPOTHESIS 1. *Medical providers will stockpile pandemic-related medications in the early stages of a pandemic.*

2.2. Price Changes of Consumer Goods During Crises

Politicians and the popular press highlight the ethical dilemma of retailers raising prices of essential goods during natural disasters (Beatty et al. 2021). Despite the attention in the press, there is scant systematic empirical evidence supporting significant price increases during crises (Cavallo et al. 2014, Heinen et al. 2019, Beatty et al. 2021, Cabral and Xu 2021). For example, like medications, gasoline demand can increase during natural disasters, but its supply is constrained in the short term. Neilson (2009) analyzes wholesale and retail prices of gasoline in a region of Texas during Hurricane Rita and shows that retail prices did not increase significantly despite substantial increases in wholesale prices of gasoline. Similarly, Beatty et al. (2021) find that gasoline retail prices do not increase beyond the increases in wholesale prices around hurricane landfalls by investigating multiple hurricane events in the U.S. In contrast, the empirical record is mixed for products with more competition. On one hand, some studies find no evidence of price increases. Beatty et al. (2019) observe no significant changes in the prices of batteries, flashlights, and bottled water before, during, and after hurricanes even with a large increase in sales prior to the forecasted landfall. Cavallo et al. (2014) show that prices of products sold in supermarkets remain stable after the earthquakes in Chile in 2010 and Japan in 2011. Gagnon and López-Salido (2020) also find no evidence of large price changes for several supermarket products associated with large swings in demand triggered by labor conflicts, mass population displacement, major snowstorms, and hurricanes. In contrast, Heinen et al. (2019)'s study of Caribbean countries shows that food and home goods prices rise in the short term following floods and hurricanes. Most relevant to our study, researchers examine price changes of selected products during the early period of the COVID-19 pandemic. Cabral and Xu (2021) analyze the price of face masks and hand sanitizers sold on Amazon and find that higher reputation sellers increase prices less than the others. Mahajan and Tomar

(2021) examine data from an online grocery retailer in India and find that the changes in prices for grocery products are minimal despite a sharp fall in product availability.

There have been selected concerns raised about medicine price increases during the COVID-19 pandemic for certain drugs such as hydroxychloroquine (Mattingly and Hogue 2020) and remdesivir (Cleary 2020), but we are unaware of any systematic assessment of changes in prescription drug prices during the pandemic. There are several additional factors that may act to restrain prescription drug price changes during a crisis. Several states have anti-price gouging laws, such as New York's General Business Law § 396-r. Furthermore, manufacturers' fairness and reputation concerns may be at play. They don't want to give the impression to consumers that they are taking advantage of the crisis by charging opportunistic prices (Kahneman et al. 1986, Gagnon and López-Salido 2020, Mahajan and Tomar 2021, Buccafusco et al. 2021, Cabral and Xu 2021). Indeed, some drug manufacturers pledged to set prices at 'nonprofit levels' during the COVID-19 pandemic (Robinson 2021). On the other hand, slack demand caused by crises might lead suppliers to reduce prices to induce demand (Gagnon and López-Salido 2020). For example, Gagnon and López-Salido (2020) find that supermarkets in the region of labor strikes experienced a drop in demand and they offered more price discounts to lure customers into their stores. So, manufacturers may lower the price of drugs not related to the pandemic disease due to a decrease in demand for non-COVID-19 care.

It is important for theory and practitioners to predict whether medication prices will rise, fall, or stay the same during a pandemic. If prices are likely to rise, stockpiling makes economic sense. However, given that most medications have a limited shelf life, excessive purchases can lead to expired medications. Furthermore, stockpiling can lead to shortages in the locations that truly need the medications. Thus, if there is limited evidence of price increases during a pandemic, policymakers and pharmacy managers would be well-advised to avoid stockpiling. Consequently, our paper empirically examines the theoretically ambiguous impact of the pandemic's advent on the prices of prescription drugs sold in the U.S. market in aggregate, by essential drug category, and by purchaser type during the initial phases of the COVID-19 pandemic. Our dataset and empirical setup allow us to study hypothetical price changes associated with both potential sudden increases in demand for COVID-19 related medications and decreases in demand for non-COVID-19 related medications. Drawing on the literature, we hypothesize that:

Hypothesis 2A. *The price of COVID-19 related medications will increase during the early stages of the pandemic.*

Hypothesis 2B. *The price of non-COVID-19 related medications will decrease during the early stages of the pandemic.*

3. Data and Empirical Methods

We obtain data from the IQVIA National Sales Perspective™(NSP) database that contains purchases of prescription drugs by pharmacies, clinics, hospitals, and other distribution channels (e.g., chain stores and food stores), aggregated to the monthly, national level. The original dataset includes over 10.38 million observations of sales of drug products from October 2014 to September 2020. Each observation includes the name of the molecule (substance) or branded name, month, sales amount in drug unit volume, sales amount in U.S. dollars, producer of the product, distribution channel, product form (e.g., oral, injectable), strength, and other information including therapeutic class, product launch date, etc. Following previously published literature (Yurukoglu et al. 2017, Conti and Berndt 2020), we refer to a drug as a group of products having the same molecule (or active ingredient) and product form. For example, lorazepam-injectable is a different drug from lorazepam-oral.

3.1. Sample Prescription Drugs

We use the U.S. Food and Drug Administration (FDA) essential medicines list to select our sample drugs. As of October 30, 2020, the FDA lists 227 essential medicines and medical countermeasures needed by acute care medical facilities to treat patients with severe injuries or illnesses, and urgent medical conditions (FDA 2020a). From this list, the pharmacist on our research team identifies 62 drugs used to care for COVID-19 patients in the same setting. Those medicines comprise what we refer to as the exposure group. We include drugs considered potentially related to COVID-19 treatments at the beginning of the pandemic, such as azithromycin, and do not include other drugs such as hydroxychloroquine, chloroquine, and tocilizumab because they are not part of the FDA essential medicines list. Then, we separate out 6 drugs that have national production quotas under the control of the U.S. Drug Enforcement Administration (DEA), leaving 56 drugs in our exposure group. Additionally, we identify drugs in the same or comparable drug categories as the exposure group drugs but which are not used for COVID-19 patients. For example, all of the sedatives in the FDA essential medicines list belong to the exposure group, so we include anesthetics in the control group because we consider anesthetics to be comparable to sedatives. We label these 58 as the control group. Thus, we have 114 sample drugs, classified as either exposure or control. The detailed sampling steps and the sample drug list are in Online Appendix A.

We extract the monthly sales of the 114 sample drugs from NSP. Because the prescription drugs used to manage severe COVID-19 patients are largely administered by physicians in clinical settings, we further focus on sales to the four major medical providers: non-federal hospitals, clinics, federal facilities, and long-term care. Sales to these four channels comprise 97.9% of the total sales to non-retail channels for our sample drugs. We exclude sales to retail pharmacies, chain stores,

food stores, mail, and all other channels. In Section 4.4.1, we run analyses with all channels and find that our results are consistent. We use two years before the start of the COVID-19 pandemic as the pre-period. Thus, our final sample ranges from January 2018 to September 2020. This yields a total of 14,754 monthly sales observations for the 114 exposure and control group drugs. Using this data, we create a drug-channel-month-year level panel data for our analyses.

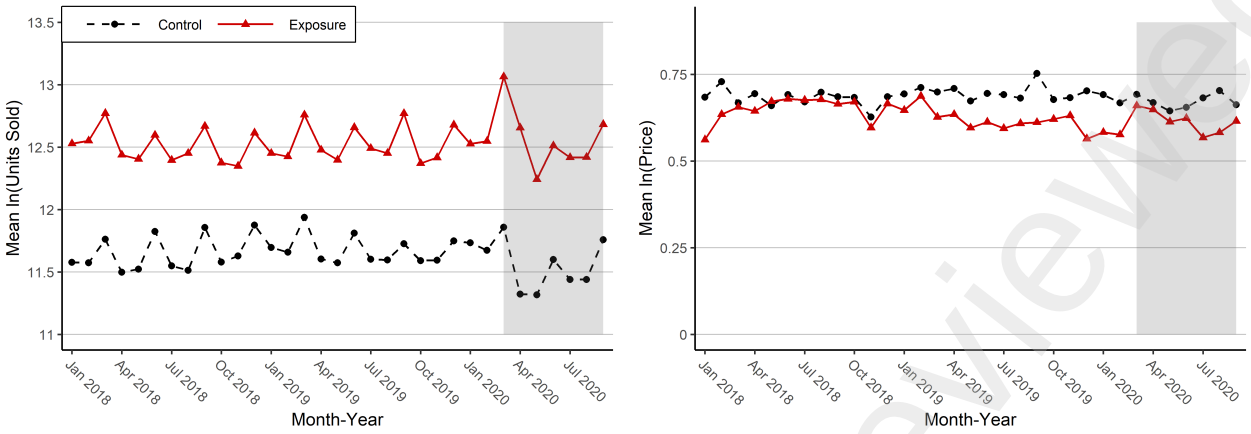
3.2. Variables

Our key outcome variable is the sales volume of a drug, $UnitsSold$, which we define as the total units of a drug sold to a channel in a month. NSP provides sales quantity in units that account for different package sizes of products. We calculate it by aggregating the units sold for all the products that belong to a drug. This definition is consistent with previous research (Yurukoglu et al. 2017, Conti and Berndt 2020) and clinical practice because medical providers view these products as close substitutes. For example, enoxaparin sodium 100mg/ml can be considered as close substitute of enoxaparin sodium 150mg/ml. In Section 4.5, we show our results are robust to defining the outcome variable at the product level, instead of drug level. To analyze changes in drug price during the initial period of the pandemic, we calculate the monthly average price per unit of a drug at a channel, $Price$, by taking the mean of unit prices of all the products that belong to the same drug by a channel. To account for the right-skewed distribution of these variables, we log-transform them in our estimations. Figure 2 plots the unadjusted means of the outcome variable by groups.

The main explanatory variables are $Exposure$ and $Post$, which are indicators for the exposure group, and the pandemic period (or post-period) from March to September 2020, respectively. We set the pandemic period starting from March 2020 as does prior research (Chua et al. 2021, Song et al. 2021) because it is when the World Health Organization declared the COVID-19 to be a pandemic, and the U.S. president declared a national emergency (CNN 2021). To capture the sales of drugs related to COVID-19 treatments, we use an interaction term, $Exposure \times Post$.

As control variables, we include the number of product varieties and the number of producers of a drug. We do not include drug price in the control variables for the sale regressions because the demand for essential drugs is not sensitive to price changes, especially for life-saving treatments during the pandemic (Lieberman et al. 2020). Our results for sales volume are robust to including price and COVID-19 hospitalizations as control variables. (See the results from the robustness checks in Online Appendix G.1). We provide descriptive statistics and correlations of variables in Online Appendix B.

Figure 2 ln UnitsSold and ln Price by Groups



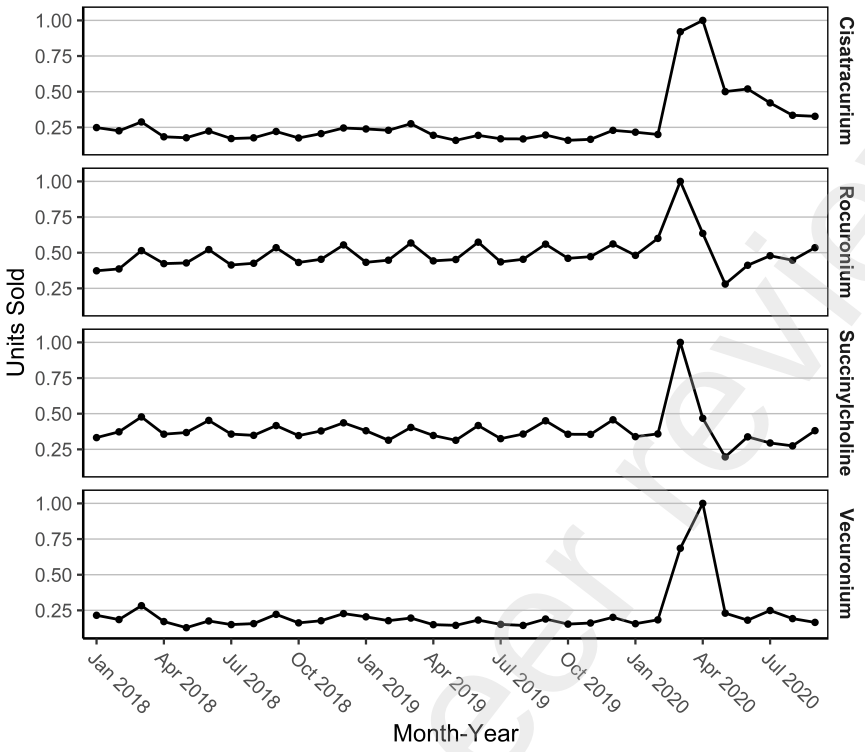
(a) ln *UnitsSold* (b) ln *Price*

Notes. Panels (a) and (b) plot the unadjusted mean of log transformed *UnitsSold* and *Price* by groups, respectively. The grey shaded area represents the COVID-19 pandemic period. *Source*: IQVIA NSP.

3.3. Econometric Specifications

A key data challenge we must overcome is isolating the portion of prescription drug sales related to COVID-19 treatments from the portion related to non-COVID-19 treatments. We need to do this because numerous reports suggest that the COVID-19 pandemic affected demand for non-COVID medical care (Alban et al. 2020, Czeisler et al. 2020, Lawrence 2020, Masroor 2020, Chua et al. 2021, Song et al. 2021, IQVIA 2021). For example, paralytic drugs provide muscle relaxation during surgery or intubation (FDA 2018). They are used to intubate COVID-19 patients who require mechanical ventilation, but are also used for surgery and intubation of non-COVID-19 patients. Many hospitals canceled elective surgeries at the start of the pandemic, decreasing the use of paralytics for non-COVID-19 treatment. If we do not account for the reduction in non-COVID-19 demand, we would underestimate COVID-19 related stockpiling of paralytics. Figure 3 plots the total sales volume of paralytics. It shows that sales surge at the beginning of the pandemic and drop shortly after. This pattern is consistent with pharmacists' suspicion that these paralytic drugs were stockpiled during the pandemic (Shuman et al. 2020). However, the net effect might be larger than the graph suggests due to the drop in elective surgeries during the pandemic. To address this issue, we use a difference-in-differences method with the control drugs that show parallel sales trends with the COVID-19 drugs before the pandemic. This enables us to more accurately identify the amount of drugs sales for the COVID-19 treatments. We assume that drug sales related to non-COVID-19 treatments for both the exposure and control groups continue parallel trends during the post-period. In Online Appendix C, we test the pre-period parallel trends, and we show that the sales (i.e. non-COVID-19 sales) and price between the groups exhibit parallel trends in the 26 months preceding the pandemic.

Figure 3 Units Sold for Paralytics



Notes. Each point represents monthly units sold of a paralytic drug to major healthcare providers (hospitals, clinics, and long-term care facilities) in the U.S. The values are normalized to the maximum value due to confidentiality. The sales increased sharply in March and April 2020, then dropped afterward. The four drugs – cisatracurium, rocuronium, succinylcholine, and vecuronium – comprise all paralytics in the FDA essential medicines list (FDA, 2020). *Source*: IQVIA NSP.

We use difference-in-differences models with fixed effects and clustered standard errors. Our baseline specification is,

$$Y_{icmy} = \alpha_i + \beta_1 Post_{my} + \beta_2 Exposure_i \times Post_{my} + \delta X_{icmy} + \lambda Month_m + \theta Channel_c + \varepsilon_{icmy}. \quad (1)$$

Here, Y_{icmy} denotes the outcome variables $\ln UnitsSold_{icmy}$, and $\ln Price_{icmy}$ for drug i, channel c, month m, and year y; α_i represents the drug fixed effects; $Post_{my}$ is an indicator variable that is equal to 1 if the month-year falls after the COVID-19 pandemic began (from March 2020) and 0 otherwise. $Exposure_i$ is an indicator variable that takes the value 1 if the drug i is used for treating COVID-19 patients. Note here that the coefficient for $Exposure_i$ is subsumed by the drug fixed effects. β_1 measures the level differences in outcome between pre- and post-period for the control group after adjusting for other covariates. The coefficient of interest is β_2, the difference-in-differences estimator, which is the difference between the change in outcome from pre- to post-period for the exposure group relative to the change in outcome from pre- to post-period for the control group, after adjusting for other covariates. X_{icmy} includes each drug's monthly number of product varieties at a channel, the monthly number of producers at a channel. We also

add drug-category-specific linear time trends to control for the sales trends of each drug category. For the drug category classification, we follow the classification in the FDA essential medicines list (FDA 2020a). An F-test of the hypothesis that the drug-category-specific trends are jointly zero is rejected in every estimation. $Month_m$ is a vector of month indicators, 1-12, such that λ captures monthly seasonality; $Channel_c$ is a vector of medical provider type (channel) indicators with θ accounting for each channel's time-invariant characteristics. It is important to control for channel effects as the level of outcome variables is significantly different by each channel, and the demand for COVID-19 treatments may vary across channels. ε_{icmy} is the idiosyncratic error. In Section 4.5, we conduct sensitivity tests to examine the robustness of our findings to specifications without control variables and other effects.

3.4. Pandemic Period Monthly Sales and Price Dynamics

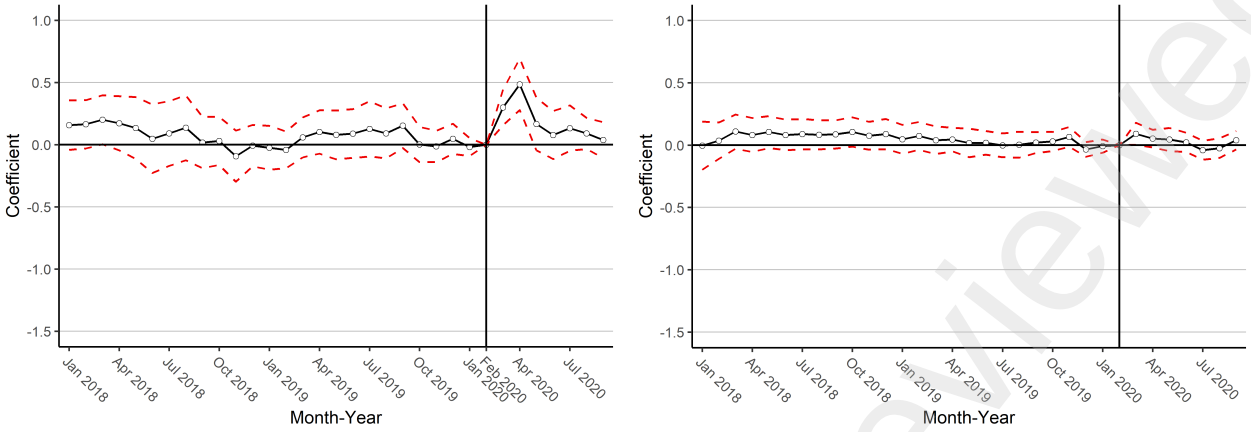
We further analyze changes in monthly drug sales and price during the early stages of the pandemic. Here, because we are interested in the dynamics at each month, we need a stronger assumption that the drug sales related to non-COVID-19 treatments and price continue parallel movements between the groups for each month of the post-period. We suppose this is a plausible assumption because first, both groups have pre-period parallel movements in sales and price as tested by analyzing the difference-in-differences estimates for the entire sample period, following Azoulay et al. (2010). As shown in Figure 4a, the movements of sales for non-COVID-19 treatments between the groups are not statistically different from each other prior to the pandemic. Second, all the drugs in our dataset are necessary to treat non-COVID-19 related medical conditions, such as heparin's use to prevent blood clots during cardiac surgery. Thus, there will be consumption of these medicines for non-COVID-19 treatments in the post-period. Therefore, we assume that the parallel movements in sales between the exposure and the control groups for non-COVID-19 purposes that we show in Figure 4a continue in the post-period. Regarding our analysis of price movements, Figure 4b illustrates that both groups have parallel movements in prices each month prior to the pandemic, which allows us to compare the post-period monthly price dynamics between the groups.

To analyze the monthly dynamics of drug sales for COVID-19 and prices, we split the discrete post-period variable into months and estimate the following model:

$$\begin{aligned} Y_{icmy} = \alpha_i + \sum_{my \in Post} \phi_{my} PostMonth_{my} + \sum_{my \in Post} \beta_{my} Exposure_i \times PostMonth_{my} \\ + \delta X_{icmy} + \lambda Month_m + \theta Channel_c + \varepsilon_{icmy}, \end{aligned} \tag{2}$$

where Y_{icmy}, α_i, $Exposure_i$, $Month_m$, $Channel_c$, X_{icmy}, and ε_{icmy} are defined as in Model (1). Here, $PostMonth_{my}$ is an indicator variable for each month in the post-period — from March to September 2020. Therefore, the coefficient ϕ_{my}, measures the difference in outcomes between the pre-period

Figure 4 Dynamics of Difference-in-Differences Estimates for Entire Period



(a) ln *UnitsSold* (b) ln *Price*

Notes. Panels (a) and (b) plot the difference-in-differences coefficients (points connected with a solid line) for each month of the entire period for the outcome variable ln *UnitsSold* and ln *Price*, respectively. Specifically, the outcome variable is regressed onto the month effects, the channel effects, drug fixed effects, control variables, and interactions of the exposure indicator with a set of indicator variables corresponding to each month with the baseline month, February 2020 (the month just before the pandemic, shown by the vertical lines). The 95% confidence interval, calculated with robust clustered standard errors, is plotted with dashed red lines.

and each month of the post-period for the control group. The coefficients of the interaction between the $Exposure_i$ and $PostMonth_{my}$ variables represent the difference-in-differences estimates. For example, the coefficient on $Exposure_i \times PostMonth_{March2020}$ is the difference between the change in outcome from pre-period to March 2020 for the exposure group relative to the change in outcome from pre-period to March 2020 for the control group, after adjusting for other covariates.

4. Results

4.1. Results: Drug Sales to Medical Providers During the Early Stages of the Pandemic

We show summary statistics in Table 3 in Online Appendix B. Note that when we refer to the mean, we use the geometric mean. Control group drugs experience decreases in monthly mean sales volume, relative to the pre-period corresponding monthly mean sales volume, from April 2020 to September 2020. On the other hand, the monthly mean sales volume of the exposure group drugs shows increases only in March (35% increase) and April 2020 (22% increase). After then, the monthly mean sales volumes are smaller than the pre-period corresponding monthly mean sales volumes, despite a significant uptick in COVID-19 patients in these months.

Column (1) of Table 1 presents the results for estimating Model (1). First, we find that the sales volume of the control group decreased significantly during the early stages of the pandemic ($\beta_1 = -0.156, p < 0.001$), which indicates that the monthly mean sales units of drugs related to non-COVID-19 treatments decreased by 14.4% ($= e^{\beta_1} - 1$) relative to before the pandemic, on average. This result is consistent with a decrease in non-COVID-19 medical care during the early period of

the pandemic (Alban et al. 2020, Czeisler et al. 2020, Lawrence 2020, Masroor 2020, Chua et al. 2021, Song et al. 2021, IQVIA 2021). Next, the difference-in-differences estimate shows a positive and statistically significant coefficient ($\beta_2 = 0.137, p < 0.05$), after controlling for other covariates. Using the coefficient, we estimate the exposure group's sales units for COVID-19 treatments as a percentage of the pre-pandemic mean sales volume. In each post-period month, about 12.6% of the exposure group's pre-period mean sales volume are sold for COVID-19 treatments on average (For details of interpretation, refer to Online Appendix D).

To analyze the monthly dynamics in sales, we estimate Model (2) and the results are summarized in column (2) of Table 1. First, the sales units of the control drugs decrease significantly relative to the pre-period mean sales units beginning with April 2020 ($\phi_{April2020} = -0.257, p < 0.001$) and reaching the lowest point in May 2020 ($\phi_{May2020} = -0.305, p < 0.001$). After May, the sales units start to recover gradually.

On the other hand, the difference-in-differences coefficients for the exposure group begin to increase from March 2020 ($\beta_{March2020} = 0.247, p < 0.01$), indicating that approximately 35.7% of the pre-period mean sales volume are sold for COVID-19 treatments in March 2020, on average[1]. Also, the difference-in-differences coefficient for April 2020 shows a statistically significant coefficient ($\beta_{April2020} = 0.433, p < 0.001$), indicating that about 38.9% of pre-period mean sales volume are sold for COVID-19 treatments in April 2020, on average. Interestingly, after April, the increases in sales volume of the exposure group begin to decrease sharply, with the difference-in-differences coefficients not significantly different from zero ($p > 0.05$ for each coefficient). The percentages of post-period sales units relative to pre-period sales units for the exposure group during these months are not statistically different from the same ratio for the control group, suggesting no significant amount of drugs are sold for COVID-19 treatments during this time period, on average across drugs and channels. This shows that the sales of drugs for COVID-19 are concentrated in the first two months of the pandemic, March and April 2020. A similar observation can be seen in Figure 4a where the difference-in-differences coefficients relative to the baseline month (February 2020) are statistically different from zero only in March and April of 2020. Considering the substantial demand for exposure group medicines from COVID-19 patients throughout the pandemic months as shown in Figure 1, our results suggest that drugs sales related to COVID-19 to medical providers precede actual demand from COVID-19 patients, evidence of stockpiling of medicines that occurs at the beginning of the pandemic. Thus, we find support for Hypothesis 1. In Section 4.3, we show that the results are not driven by supply shortages and are consistent across different major drug categories.

[1] Because of the significant month effects on sales as seen in Figure 2a and as we verify in our regressions, we estimate monthly sales volume for COVID-19 treatments relative to the pre-period mean monthly sales volume by accounting month effects. Precisely, we use the formula, $e^{(\beta_{my}+\phi_{my}+\lambda_m)} - e^{(\phi_{my}+\lambda_m)}$.

Table 1 Analyses of Changes in Sales Volume and Price During the Early Stages of the Pandemic

Outcome Variable	ln *UnitsSold*		ln *Price*	
Explanatory Variable	(1)	(2)	(3)	(4)
Post	-0.156***	-	-0.002	-
	(0.034)		(0.024)	
March 2020		0.021		-0.016
		(0.059)		(0.027)
April 2020		-0.257***		0.006
		(0.056)		(0.025)
May 2020		-0.305***		-0.007
		(0.054)		(0.031)
June 2020		-0.199***		0.004
		(0.047)		(0.026)
July 2020		-0.158***		0.018
		(0.047)		(0.029)
August 2020		-0.113*		0.004
		(0.054)		(0.030)
September 2020		-0.075		-0.024
		(0.051)		(0.032)
Exposure × *Post*	0.137*	-	-0.010	-
	(0.058)		(0.041)	
Exposure × *March* 2020		0.247**		0.051
		(0.080)		(0.044)
Exposure × *April* 2020		0.433***		0.014
		(0.094)		(0.044)
Exposure × *May* 2020		0.115		0.008
		(0.080)		(0.052)
Exposure × *June* 2020		0.028		-0.015
		(0.079)		(0.049)
Exposure × *July* 2020		0.084		-0.077
		(0.074)		(0.052)
Exposure × *August* 2020		0.042		-0.060
		(0.071)		(0.051)
Exposure × *September* 2020		-0.010		0.004
		(0.068)		(0.052)
Number of Producers	0.121*	0.121*	-0.015	-0.015
	(0.056)	(0.056)	(0.015)	(0.015)
Number of Prod. Variety	0.011	0.011	0.008*	0.009*
	(0.014)	(0.014)	(0.004)	(0.004)
Month effects	Yes		Yes	
Channel effects	Yes		Yes	
Drug category × time trends	Yes		Yes	
Adjusted R^2	0.530	0.530	0.043	0.043
No. of drugs (exposure group)	56		56	
No. of drugs (control group)	58		58	
Observations	14,754		14,754	

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

4.2. Results: Changes in Prices of Essential Prescription Drugs During the Early Stages of the Pandemic

We analyze the changes in prices of the drugs by estimating Models (1) and (2) with the outcome variable, $\ln Price$. The objective of the analysis is to characterize how drug price changes relative to temporary demand changes due to the onset of the pandemic. We present the results in columns (3) and (4) of Table 1. We find that the control group drugs do not show a statistically significant percent change in price during the post-period ($\beta_1 = -0.002, p > 0.1$). Thus, Hypothesis 2B is not supported. For the exposure group, the difference-in-differences coefficient in column (1) shows that the exposure group has no significant change in price relative to the control group during the post-period ($\beta_2 = -0.010, p > 0.1$). Thus, Hypothesis 2A is also not supported. Likewise, the post-period monthly price dynamics in column (4) do not present statistically significant coefficients in every post month for both groups, suggesting that the market price of essential drugs at the national level is not responsive to the sudden demand increases and decreases that we observe in the sales volume analyses in Section 4.1.

4.3. Alternative Explanations

In this section, we explore two potential alternative explanations of our main results: (a) supply shortages during the early period of the pandemic and (b) differences across drug categories of their relevance to COVID-19 treatment.

4.3.1. Alternative Explanation 1: Supply Shortages During the Pandemic

An alternative explanation of our results is that the decreases in sales volume of COVID-19 drugs that we observe after April 2020 are due to supply shortages rather than stockpiling by medical providers. If this is the case, we would expect the sales volume of drugs without supply shortages in our exposure group to consistently appear significantly higher than the control group's sales volume. To rule out this explanation, we estimate Models (1) and (2) by stratifying our exposure group drugs into three groups: drugs that had shortages before and during our study period ($n = 8$), drugs that had shortages that began after the pandemic ($n = 11$), and drugs that did not have any shortages during our study period ($n = 37$). Some of the drugs in the control group had shortages before and/or during the post-period, so we exclude them from this analysis. We identify the list of drugs that experienced shortages using the FDA drug shortages database (FDA 2020b). This database lists products whose overall market demand is not being met by the manufacturers (FDA 2020b). Based on the database, we label a drug in our sample 'in shortage' if any of the products within the drug experienced shortage. We report the shortage status in the last column of Table 2 in Online Appendix A. The analysis results are reported in columns (1) to (6) of Table 2.

First, the exposure group drugs with shortages that start before the pandemic show an insignificant increase in sales during the post-period ($\beta_2 = 0.047, p > 0.1$) relative to the control group,

as shown in column (1). The monthly difference-in-differences coefficients in column (2) also show relatively small and insignificant coefficients throughout the post-period. Given that the shortages of these drugs lasted during the post-period, the results suggest that the supply disruptions affected the sales in the early period of the pandemic.

Next, the exposure group drugs with shortages that began during the pandemic show an insignificant difference-in-differences coefficient ($\beta_2 = 0.188, p > 0.1$) for the overall pandemic period in column (3). On the other hand, the monthly dynamics analysis in column (4) shows that the sales increases were highly concentrated in March ($\beta_{March2020} = 0.380, p < 0.05$), and April 2020 ($\beta_{April2020} = 0.869, p < 0.001$), while the difference-in-differences coefficients after April 2020 are statistically insignificant. Considering that the shortages of drugs in this group started after April 2020 and they are demand-driven rather than driven by supply disruptions as indicated in the FDA drug shortages database (FDA 2020b), the results support that the abrupt increase in demand due to stockpiling at the beginning of the pandemic caused the nationwide shortages.

The sales of exposure group drugs without any shortages also show the stockpiling pattern. In column (5), the sales volume shows a significant increase ($\beta_2 = 0.155, p < 0.05$) relative to the control group, and the increase in sales occur only in the first two months ($\beta_{March2020} = 0.260, p < 0.01$; $\beta_{April2020} = 0.382, p < 0.001$), as shown in column (6). The implication of this analysis is that the lack of sales increase in later pandemic months is not due to a supply shortage: the manufacturers had enough capacity to meet the surged demand for these drugs at the start of the pandemic. This result shows the U.S. pharmaceutical supply chain has some resiliency. Overall, the results suggest that the decrease in sales related to COVID-19 treatments after April of 2020 is mainly due to stockpiling rather than supply shortages.

Additionally, we analyze price changes of drugs based on the shortage status and the results are presented in columns (7) to (12). To summarize, the results show that the price of drugs does not change significantly during the overall post-period as the difference-in-differences coefficients do not show statistical significance in columns (7), (9), and (11). As shown in column (9), price increases for a few drugs with shortages that began during the pandemic. However, the increase is not widespread across drugs as the difference-in-differences coefficient is not significant ($\beta_2 = 0.164, p > 0.1$).

Another interesting observation is that the price of drugs without any shortages during the post-period does not respond to demand surges in March and April of 2020 ($\beta_{March2020} = 0.021, p > 0.1$; $\beta_{April2020} = -0.026, p > 0.1$). However, prices significantly decreased in June and July of 2020 in response to decreases in demand ($\beta_{June2020} = -0.082, p < 0.05$; $\beta_{July2020} = -0.113, p < 0.05$).

These results suggest that although a few of the drugs in our sample do experience substantial changes in price, the changes are not widespread across drugs and channels.

Table 2 Stratified Analyses by Shortage Status

Outcome Variable	ln *UnitsSold*						ln *Price*					
Shortage Status	Drugs with shortages before and during the pandemic		Drugs with shortages began during the pandemic		Drugs without shortages		Drugs with shortages before and during the pandemic		Drugs with shortages began during the pandemic		Drugs without shortages	
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post	-0.167***	-	-0.133***	-	-0.191***	-	-0.043+	-	-0.038	-	-0.004	-
	(0.037)		(0.042)		(0.038)		(0.023)		(0.025)		(0.026)	
March 2020		-0.033		0.005		-0.015		-0.039		-0.045		-0.006
		(0.067)		(0.064)		(0.070)		(0.024)		(0.026)		(0.029)
April 2020		-0.295***		-0.251***		-0.311***		-0.012		-0.008		0.025
		(0.060)		(0.061)		(0.066)		(0.026)		(0.027)		(0.027)
May 2020		-0.302***		-0.261***		-0.346***		-0.052		-0.047		-0.012
		(0.057)		(0.061)		(0.061)		(0.036)		(0.035)		(0.036)
June 2020		-0.221***		-0.190***		-0.243***		-0.035		-0.033		0.000
		(0.048)		(0.052)		(0.052)		(0.024)		(0.025)		(0.026)
July 2020		-0.155**		-0.127*		-0.179***		-0.035		-0.028		0.011
		(0.058)		(0.063)		(0.052)		(0.032)		(0.034)		(0.032)
August 2020		-0.114		-0.083		-0.140*		-0.059*		-0.040		-0.010
		(0.079)		(0.082)		(0.062)		(0.025)		(0.030)		(0.029)
September 2020		-0.057		-0.007		-0.103+		-0.066*		-0.065+		-0.031
		(0.064)		(0.069)		(0.060)		(0.032)		(0.037)		(0.035)
Exposure × *Post*	0.047	-	0.188	-	0.155*	-	0.006	-	0.164	-	-0.051	-
	(0.126)		(0.167)		(0.066)		(0.061)		(0.124)		(0.040)	
Exposure × *March* 2020		0.079		0.380*		0.260**		0.120		0.104		0.021
		(0.178)		(0.152)		(0.093)		(0.137)		(0.112)		(0.041)
Exposure × *April* 2020		0.180		0.869***		0.382***		-0.121		0.219+		-0.026
		(0.204)		(0.218)		(0.104)		(0.111)		(0.122)		(0.039)
Exposure × *May* 2020		-0.076		0.165		0.166+		0.152		0.218		-0.079+
		(0.157)		(0.189)		(0.092)		(0.123)		(0.142)		(0.048)
Exposure × *June* 2020		0.050		-0.091		0.067		0.111		0.157		-0.082*
		(0.166)		(0.217)		(0.085)		(0.115)		(0.158)		(0.038)
Exposure × *July* 2020		0.062		0.067		0.091		-0.075		0.147		-0.113*
		(0.122)		(0.231)		(0.080)		(0.132)		(0.128)		(0.056)
Exposure × *August* 2020		0.028		-0.071		0.091		-0.040		0.104		-0.083
		(0.124)		(0.191)		(0.079)		(0.117)		(0.129)		(0.056)
Exposure × *September* 2020		0.005		-0.111		0.016		-0.125		0.202		0.002
		(0.127)		(0.202)		(0.078)		(0.122)		(0.146)		(0.055)
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Month effects	Yes		Yes		Yes		Yes		Yes		Yes	
Channel effects	Yes		Yes		Yes		Yes		Yes		Yes	
Drug category × time trends	Yes		Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.526	0.526	0.502	0.502	0.487	0.487	0.045	0.045	0.074	0.073	0.100	0.100
No. of drugs (exposure group)	8		11		37		8		11		37	
No. of drugs (control group)	48		48		48		48		48		48	
Observations	7,135		7,505		10,953		7,135		7,505		10,953	

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Control variables include the number of producers and the number of product variety. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

4.3.2. Alternative Explanation 2: Differences in Relevance to COVID-19 Treatments across Drug Categories

Another alternative explanation is that a subset of the COVID-19 treatment drugs was considered useful at the beginning of the pandemic but subsequently showed a lack of efficacy. This subset of drugs might be responsible for the pattern we see in the data: a sudden increase in sales volume early in the pandemic followed by a decrease in later periods. We examine and ultimately rule out this explanation by conducting stratified analyses by the subset of major drug categories that were consistently used for COVID-19 treatments (e.g., paralytics, anti-microbials, and sedatives). If the stockpiling pattern appears for those consistently used COVID-19 drug categories, it confirms that our finding of stockpiling is not from the drugs that were found to lack efficacy at treating COVID-19 patients. Furthermore, we explore heterogeneity in the sales increases and price changes across the major drug categories. We do this because demand for each category may differ and our results, therefore, might stem from a few drugs rather than being a widespread effect.

The results, shown in columns (1) through (6) of Table 3, verify that the sales related to COVID-19 treatments are concentrated in the early period of the pandemic for each of these categories. All the major categories show large and statistically significant monthly difference-in-differences coefficients in March and April of 2020. After then, the coefficients of 4 out of 5 months from May 2020 to September 2020 do not show statistical significance across the three drug categories, indicating that the sales volume of the major categories decreased sharply. The results buttress that the sales volume for COVID-19 related medications are highly concentrated in the early months of the pandemic for drugs consistently used throughout the pandemic. Using Wald tests, we confirm that the monthly difference-in-differences coefficients of March 2020 and April 2020 are statistically larger than the coefficients of months from June 2020 to September 2020, for three drug categories, except for sedatives in July 2020.

Columns (7) to (12) show the analyses of price changes of these major drug categories relative to control group drugs. Paralytics increase in price ($\beta_2 = 0.116,\ p < 0.01$) during the post-period, on average. This may be because they experienced the largest demand increases during the early period of the pandemic. On the other hand, as shown in columns (9) and (11), prices remain constant throughout the post-period for anti-microbials ($\beta_2 = -0.080,\ p > 0.1$) and sedatives ($\beta_2 = 0.035,\ p > 0.1$). Furthermore, despite substantial upticks in sales volume in March and April 2020, price remain constant for these two categories during those months, as columns (10) and (12) show (for anti-microbials, $\beta_{March2020} = 0.040,\ p > 0.1,\ \beta_{April2020} = -0.009,\ p > 0.1$; for sedatives, $\beta_{March2020} = -0.061,\ p > 0.1,\ \beta_{April2020} = 0.085,\ p > 0.1$).

Table 3 Stratified Analyses by Major Drug Categories

Outcome Variable	ln *UnitsSold*						ln *Price*					
Drug Category	Paralytics		Anti-microbials		Sedatives		Paralytics		Anti-microbials		Sedatives	
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post	-0.160***	-	-0.178***	-	-0.163***	-	-0.024	-	-0.005	-	-0.024	-
	(0.035)		(0.035)		(0.031)		(0.021)		(0.023)		(0.021)	
March 2020		0.020		0.001		0.026		-0.031		-0.015		-0.028
		(0.059)		(0.065)		(0.058)		(0.026)		(0.026)		(0.026)
April 2020		-0.250***		-0.267***		-0.254***		-0.015		0.009		-0.007
		(0.059)		(0.063)		(0.058)		(0.021)		(0.024)		(0.021)
May 2020		-0.291***		-0.330***		-0.308***		-0.030		-0.012		-0.019
		(0.052)		(0.054)		(0.051)		(0.032)		(0.032)		(0.033)
June 2020		-0.217***		-0.231***		-0.215***		-0.021		-0.008		-0.013
		(0.047)		(0.047)		(0.044)		(0.023)		(0.024)		(0.024)
July 2020		-0.155**		-0.176***		-0.178***		0.002		0.013		-0.021
		(0.053)		(0.049)		(0.050)		(0.030)		(0.029)		(0.029)
August 2020		-0.128+		-0.134*		-0.124*		-0.026		0.002		-0.029
		(0.068)		(0.057)		(0.062)		(0.025)		(0.028)		(0.025)
September 2020		-0.079		-0.106+		-0.075		-0.047		-0.020		-0.057
		(0.061)		(0.057)		(0.057)		(0.030)		(0.032)		(0.031)
Exposure × *Post*	0.504**	-	0.169	-	0.288**	-	0.116**	-	-0.080	-	0.035	-
	(0.155)		(0.105)		(0.098)		(0.035)		(0.053)		(0.051)	
Exposure × *March* 2020		0.726**		0.360**		0.478**		0.123**		0.040		-0.061
		(0.226)		(0.112)		(0.172)		(0.078)		(0.049)		(0.063)
Exposure × *April* 2020		1.448***		0.420***		0.672**		0.121***		-0.009		0.085+
		(0.318)		(0.111)		(0.255)		(0.038)		(0.057)		(0.051)
Exposure × *May* 2020		0.521**		0.099		0.162		0.192		-0.067		-0.011
		(0.190)		(0.141)		(0.118)		(0.045)		(0.063)		(0.101)
Exposure × *June* 2020		0.215		0.028		0.013		0.032		-0.134*		0.059
		(0.185)		(0.138)		(0.106)		(0.063)		(0.054)		(0.057)
Exposure × *July* 2020		0.169		0.112		0.287+		0.160*		-0.189*		-0.004
		(0.178)		(0.135)		(0.172)		(0.074)		(0.088)		(0.069)
Exposure × *August* 2020		-0.035		0.088		0.180**		0.034		-0.144+		0.052
		(0.154)		(0.118)		(0.066)		(0.069)		(0.081)		(0.109)
Exposure × *September* 2020		0.036		0.056		0.064		0.139*		-0.069		0.176**
		(0.160)		(0.130)		(0.081)		(0.069)		(0.074)		(0.065)
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Month effects	Yes		Yes		Yes		Yes		Yes		Yes	
Channel effects	Yes		Yes		Yes		Yes		Yes		Yes	
Drug category × time trends	Yes		Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.506	0.507	0.519	0.520	0.506	0.506	0.056	0.056	0.055	0.052	0.061	0.061
No. of drugs (exposure group)	4		17		8		4		17		8	
No. of drugs (control group)	58		58		58		58		58		58	
Observations	7,911		9,642		8,442		7,911		9,642		8,442	

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Control variables include the number of producers and the number of product variety. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

4.4. Additional Analyses

We conduct additional analyses to explore whether stockpiling appears in retail pharmacies and other channels that we exclude from our main analyses. We also examine sales volume and price in those channels. In addition, we analyze the sales of drugs that have DEA national production quotas to characterize sales patterns of drugs that cannot be stockpiled freely due to government restrictions on production and purchase quantities that limit sudden increases in supply or demand.

4.4.1. Extended Analysis with All Channels

We repeat our analyses by extending sales data to the previously omitted channels including the following: retail pharmacies, HMO, home medical, chain stores, mail order, and all other channels. We do this to explore whether stockpiling of the exposure drugs occurs outside of the hospital setting. As the results shown in Table 6 in Online Appendix E demonstrate, the coefficient of interest in column (1) loses statistical significance ($\beta_2 = 0.053$, $p > 0.1$). This result suggests that the sales of exposure group drugs are concentrated with the major medical providers rather than other channels. This may be because the pharmacologic interventions for confirmed COVID-19 patients are mostly provided in the inpatient clinical setting (NIH 2020). Column (2) shows that the monthly difference-in-differences coefficient for March 2020 is insignificant ($\beta_{March2020} = 0.108$, $p > 0.1$), April 2020 is significant ($\beta_{April2020} = 0.316$, $p < 0.01$), while the coefficients from May 2020 to September 2020 are not statistically different from 0. Thus, the increase in sales of the exposure group drugs are also concentrated in the early period of the pandemic, suggesting that, although the other channels lag a month behind the major medical providers, stockpiling occurred in the other channels.

Columns (3) and (4) of Online Appendix E Table 6 displays consistent results for the price analyses. Changes in price during the post-period relative to the pre-pandemic period are not significant for both groups, even in this extended sample ($\beta_1 = 0.001$, $p > 0.1$; $\beta_2 = -0.014$, $p > 0.1$).

4.4.2. Analysis of Drugs with Production Quotas

To provide further evidence that COVID-19 drugs are stockpiled at the beginning of the pandemic, in this section, we contrast the sales pattern of drugs that cannot be stockpiled freely with the stockpiling pattern shown for COVID-19 drugs. More specifically, we analyze the sales of drugs under DEA's national drug control policy, which limits production and purchase quantities of highly addictive medicines ("controlled substances"). DEA quotas limit the quantity of certain controlled substances by establishing annual aggregate production quotas which are allocated among registered manufacturers (DEA 2017). In addition, DEA also limits the quantity of controlled substances that hospitals can purchase each month, with allotments based on prior usage. Pertinent to our study, purchasing controls make it difficult to drastically increase purchase

quantities, limiting medical providers' ability to stockpile. For example, wholesalers have monitoring programs to prevent large orders, see McKesson (2021). The initial sample of exposure group drugs contains 6 drugs (analgesics) that are controlled by DEA due to high risk of overdose and addiction: fentanyl (injectables), hydromorphone (injectables, orals), morphine (injectables, orals), and oxycodone (orals). In other words, these COVID-19 treatment drugs have DEA production quotas. Note that in response to the demand surge during COVID-19, in early April 2020, DEA increased production quotas by 15% for fentanyl, hydromorphone, and morphine (Department of Justice 2020). Nonetheless, except for oxycodone (orals), the FDA drug shortages database (FDA 2020b) shows that the DEA drugs in our sample were in shortage before and during the pandemic. Thus, buyers could not stockpile these medicines freely because demand exceeded supply. Figure 1 in Online Appendix F plots the unadjusted means of the outcome variables with this new group: DEA-controlled exposure group. Online Appendix F Figure 1a shows that the DEA-controlled exposure group drugs' sales volume exhibits a slightly decreasing linear trend during the pre-pandemic period, and Online Appendix F Figure 1b shows that the price of the DEA-controlled exposure group fluctuates more than the other groups. Therefore, we test the pre-period parallel movements of sales and price between the DEA-controlled exposure group drugs and the control group as depicted in Figure 2 in Online Appendix F. After confirming the parallel movements assumption, we estimate Models (1) and (2). For brevity, the results are presented in Online Appendix F Table 7.

The monthly difference-in-differences coefficients for the DEA-controlled exposure group show positive and statistically significant estimates for every post-period month after adjusting for other covariates (e.g., difference-in-differences estimates are greater than 0.2 in every post-period month). In contrast to our main result, the DEA-controlled medicines retain significant amounts of sales volume increases related to COVID-19 throughout the post-period. This result indicates that the DEA's policy restrains stockpiling at the beginning of the pandemic and instead induces a consistent increase in sales for COVID-19 treatments throughout the later pandemic months. Based on this analysis as a counterexample of stockpiling, we argue that the sales patterns of the exposure group drugs in Section 4.1 would appear as that of the DEA-controlled drugs in the absence of stockpiling. Lastly, monthly prices of DEA-controlled drugs do not show significant changes during the post-period months in our sample despite COVID-19 related sales increases.

4.5. Robustness Checks

We run additional analyses to examine the robustness of our results. We report detailed results in Online Appendix G. First, we explore the sensitivity of our estimates by including and excluding control variables and other effects. The results for the outcome variable $\ln UnitsSold$ are summarized in Table 8 and Table 9 in Online Appendix G.1, and the results for the outcome variable

$\ln Price$ are summarized in Table 10 and Table 11 in Online Appendix G.1. In short, we find the coefficients of interest do not fluctuate much compared to the main specification except for column (4) which is the specification without channel fixed effects. Because there exists heterogeneity in sales and prices across channels and adding channel effects significantly increases the explanatory power, our preferred specification includes channel effects. In the analysis of $UnitsSold$, we also include the monthly COVID-19 hospitalizations (column 5) and average drug price (column 6) in the control variables, and we verify that our estimates do not change significantly by including them. Here, we proxy demand for COVID-19 drugs by using the number of monthly hospitalized patients with COVID-19 at $t+1$. We extract COVID-19 hospitalization data from The COVID Tracking Project at *The Atlantic* (Atlantic 2020). We use COVID-19 hospitalizations one month after sales occurred as a control variable rather than hospitalizations during the same month because our pharmacist partner reports that hospital-based medical providers purchase COVID-19 medications based on predictions of future inpatient demand extrapolated from the number of positive COVID-19 tests in their community rather than waiting until COVID-19 infected patients become inpatients in the hospital. Furthermore, they keep few weeks of supplies on hand to account for supply chain lead times. We should note that the COVID-19 hospitalizations variable is highly correlated with the monthly interaction terms in our Model (2), and for this reason, we do not include this variable in our main analyses.

Next, we repeat our analyses using an alternative outcome variable, $SalesAmount$, which is the total amount of sales measured in U.S. dollars of a drug to a channel in a month-year. The results are presented in Online Appendix G.2 Table 12. We find consistent results that the sales of drugs for COVID-19 treatments are concentrated only in the first two months of the pandemic ($\beta_{March2020} = 0.288, p < 0.01$; $\beta_{April2020} = 0.449, p < 0.001$).

Third, as a specification test, Models (1) and (2) are estimated with random effects instead of fixed effects at the drug level. The results are presented in Online Appendix G.3 Table 13 and we find that our main results are robust to random effects specifications.

Fourth, we run analyses of sales and price measured at the product-channel-month-year level, rather than at the drug-channel-month-year level. Here we define the product unit of analysis based on the molecule's unique national drug code. The new panel data at the product-channel-month-year level have 209,653 observations for 2,659 unique products that belong to our 114 sample drugs. The detailed results can be found in Online Appendix G.4 Table 14 and we verify our results that sales increases of our exposure group drugs relative to the control group are concentrated only in the first two months of the pandemic, in column (2), with difference-in-differences coefficients for March 2020 and April 2020 ($\beta_{March2020} = 0.129, p < 0.001$; $\beta_{April2020} = 0.191, p < 0.001$). We also find consistent results for price change analyses that the price of the control group does not

show a significant decrease during the post-period ($\beta_1 = -0.006, p > 0.1$); the price of the exposure group does not have a statistically significant increase during the overall post-period relative to the control group ($\beta_2 = 0.000, p > 0.1$). Likewise, all of the monthly difference-in-differences coefficients in column (6) are not statistically different from 0, except for March 2020, which shows a marginally significant positive coefficient ($\beta_{March2020} = 0.025, p < 0.1$). The results confirm that there were no widespread price changes of the drugs in our sample despite significant changes in sales volume in the early period of the pandemic.

Lastly, we run placebo tests by randomly selecting an exposure group of 56 drugs and randomly assigning placebo pandemic months. We then repeat the estimation of Model (1) 100 times for the outcome variable, $\ln UnitsSold$. As plotted in Online Appendix G.5 Figure 5, the results show that none of the 100 placebo models produces statistically significant positive coefficients, while 3 models yield statistically significant negative coefficients. This supports that the significant impact on drug sales volume that we find is not spurious (Bavafa et al. 2018, Song et al. 2018, Liu and Bharadwaj 2020).

5. Discussion and Conclusions

Using U.S. national sales data of essential medicines, we show that the sales of drugs related to COVID-19 treatments are concentrated in the first two months of the pandemic, during which time sales peak. Sales drop in the third month and beyond. Additionally, we find that price remains stable throughout the early period of the pandemic. We conduct rigorous empirical analyses to demonstrate that the results reflect stockpiling of drugs by medical providers across the nation at the beginning of the pandemic. Moreover, we provide estimates of increases in sales for exposure group drugs and decreases for control group drugs during the early stages of the pandemic. On average, sales volume of COVID-19-related drugs increases by 55% during the first 2 months of the pandemic. In terms of magnitude, we estimate that the volume of drug sales for COVID-19-related treatments during these two months is about 75% of the pre-period monthly average volume. After then, monthly sales volumes are smaller than pre-pandemic monthly averages, despite a significant uptick in COVID-19 hospitalized patients in these months. In contrast, demand for non-COVID-19-related drugs decreases by 14.4% from March 2020 through September 2020, relative to the pre-pandemic period. We also find that the prices of drugs used to treat COVID-19 do not change substantially despite significant increases in demand during the pandemic. Although scholars raise concerns about drug price gouging during the pandemic (Mattingly and Hogue 2020, Cleary 2020), we find no evidence that drug manufacturers raise prices across the COVID-19 drugs, channels, and pandemic months. Relatedly, the prices of non-COVID-19-related drugs do not decrease substantially, despite the decrease in demand due to hospitals canceling elective surgery

and other treatments not related to COVID-19. Thus, our results suggest that the impact of price changes on drug purchases is minimal during the early period of the pandemic for U.S. medical institutions.

5.1. Implications for Theory

The paper contributes to the supply chain management literature on stockpiling in anticipation of supply shortages. Our study complements this body of literature by adding empirical evidence of stockpiling by medical providers during a global pandemic. Our results are in line with supply chain management theory that predicts that orders and sales will be inflated and placed ahead of demand when there is an expected constrained supply, such as occurred during the COVID-19 pandemic (Lee et al. 1997a,b, Cachon and Lariviere 1999, Armony and Plambeck 2005, Sterman and Dogan 2015, Bray et al. 2019). Examining stockpiling behavior by hospitals empirically is challenging because consumption or inventory is often unobservable (Hendel and Nevo 2006). Our paper is one of a few to use field empirical data to document stockpiling behavior in anticipation of supply interruptions. The first empirical paper in this space is Bray et al. (2019), which uses supermarket chain data to show that retailers order more often as a hoarding strategy when the upstream inventory level is low. Our results differ from Bray et al. (2019) because we show that, in our setting, stockpiling is triggered instead by an upswing of demand. We expand the generalizability of Bray et al. (2019) by examining stockpiling behavior in a very different setting: pharmaceutical supply chains during a global pandemic.

Our study also contributes to the Economics literature on price changes during crises. Prior literature provides ambiguous empirical evidence of price changes during unexpected demand changes created by natural disasters. Our results are inconsistent with recent evidence of price increases during the COVID-19 pandemic for retail products (Cabral and Xu 2021); the abrupt increase in prices for unproven drugs for COVID-19 treatments touted by the media (Marsh 2020); and a recent report that drug manufacturers raised prices on more than 860 drugs by about 5% in the year 2020 to make up for lost revenue as prescriptions plummeted during the global lockdown (Erman and O'Donnell 2020). We speculate that manufacturers of COVID-19 related medications have strong fairness concerns during the pandemic which stifle price increases because many of the medications are closely related to the well-being of the public and received significant attention from the mass media. Thus, our results are consistent with previous empirical research that shows price gouging does not always occur during the time of crisis (Neilson 2009, Cavallo et al. 2014, Beatty et al. 2019, 2021, Gagnon and López-Salido 2020).

5.2. Implications for Practice

Our study provides valuable information that can help manufacturers better forecast demand during future pandemics. Stockpiling is one cause of the bullwhip effect because it introduces extreme variability that propagates up the supply chain (Lee et al. 1997a,b, Su 2010, Sterman and Dogan 2015, Bray et al. 2019). Our conclusions suggest that orders due to stockpiling by downstream buyers early on in a pandemic period should be discounted when predicting future demand. This is an important finding that can help manufacturers avoid excess inventory production during a pandemic. To illustrate the folly of not discounting the uptick in sales due to stockpiling, Fastenal, a supplier of facial masks and disposable respirators, invested in increasing production in early 2020 only to be stuck with $30 million in slow moving inventory in 2020 Q3 (Florness 2020).

Our results also provide estimates of the substantial decrease in sales that other essential drugs not related to the pandemic disease might experience. Drug manufacturers could use our result to confidently repurpose non-pandemic-related drug production lines to instead produce drugs used for the pandemic disease.

Our finding that hospitals preemptively stockpiled COVID-19 related drugs is important because stockpiling drugs during a national health crisis could negatively affect human life. First, hotspots with patient surges can experience shortages or delays in procurement of drugs which then lead to suboptimal patient outcomes. Indeed, during the first period of the COVID-19 pandemic, orders were not fulfilled based on actual need or whether the facilities were in a hotspot. This caused shortages of essential COVID-19 drugs in hard-hit regions, such as New York (Gibney and Zipp 2020, Rowland and Slater 2020). Furthermore, with a global pandemic and interconnected global supply chains, stockpiling of drugs by U.S. medical providers could worsen shortages of drugs in other parts of the world. For example, there were drug shortages in Europe (Stephenson 2020) and Brazil (Pedroso and Reverdosa 2021) during the pandemic. Next, stocking up on drugs can increase inventory costs for organizations that otherwise would keep only a few weeks of supply on hand. For example, a hospital pharmacist we spoke with reported his/her hospital's extra purchasing at the beginning of the pandemic resulted in a conference room filled to the ceiling with medicines that ultimately were not needed.

Finally, the nationwide scale of our dataset creates actionable insights for pharmacists and purchasing managers at hospitals. The strong evidence of no significant drug price increases during a pandemic for essential generic drugs eliminates one motivation of stockpiling: expected price increases due to a health crisis. In addition, our results on stockpiling of drugs that didn't have nationwide shortages in Section 4.3.1 suggest that hospital managers should not have stocked up on certain medications that the suppliers had enough capacity to meet the surged demand during the early stages of the pandemic.

5.3. Implications for Policymakers

Our analyses offer four important policy implications related to pharmaceutical supply chains. First, we provide a methodological approach that can be used to more accurately quantify pandemic disease-related demand surges by teasing out demand for non-pandemic treatments from total sales. The White House (2021, p. 243) sets pandemic-related demand prediction as a near-term step and will assemble a consortium of public health experts to determine the demand increase of critical drugs. Our method can be helpful to prepare a virtual strategic stockpile of active pharmaceutical ingredients as the COVID-19 exposes the lack of supplies in the U.S. Strategic National Stockpile (GAO 2020, Fitzpatrick 2020, Gerstein 2020). The virtual stockpile will involve contracts with ingredient suppliers that require them to hold surplus inventory as well as to possess surge manufacturing capacity (The White House 2021, p. 247). Strategic National Stockpiles of medicines, in general, may be wasteful due to the short shelf life of medicines. Therefore, manufacturers of critical medications could instead be required to keep more safety stock on hand. For example, Australia has a recent policy requiring pharmaceutical companies to hold four to six months of stock for critical medicines onshore (Scott 2021). To help create a resilient drug supply, The White House (2021) plans to invest in onshoring the production of essential medicines within the U.S. or its close allies (p. 241-243), and to invest in developing innovative manufacturing processes (e.g., continuous manufacturing, portable and modular manufacturing platforms) (p. 244-245).

Second, our study reiterates the urgency of building transparent pharmaceutical supply chains. Many experts criticize the lack of information sharing across drug supply chains (Woodcock and Wosinska 2013, Fox et al. 2014, Gibson and Singh 2018, FDA 2019, Schondelmeyer et al. 2020, The White House 2021). These factors are perceived as a major cause of increasing anxiety of medical providers, triggering stockpiling, which in turn contributes to drug shortages during the pandemic (Gibney and Zipp 2020, Premier Inc. 2020, Thomas 2020). Upstream suppliers sharing capacity information with buyers could help alleviate buyers' anxiety, lessen competition among buyers (Lee et al. 1997a,b), and reduce stockpiling. As a step in this direction, the U.S. Department of Health and Human Services initiated the Supply Chain Control Tower during the pandemic to monitor the supply of critical medical products by collecting information from manufacturers, distributors, and medical providers (The White House 2021). Still, this initiative relies on distributors voluntarily sharing data, and it is unclear whether the information will continue to be available after the COVID-19 public health emergency (The White House 2021, p. 233). For the supply side, increased transparency among pharmaceutical firms can incentivize competitors to increase the supply of drugs that are in shortage (Lee et al. 2021). Moreover, transparency of demand information is necessary for distributing essential medicines based on patient demand rather than on orders from medical providers.

Third, our study suggests the need for regulation to prevent stockpiling of essential medicines. This could take the form of policies like those used by wholesalers to prevent over-ordering of DEA-controlled drugs (e.g., see McKesson (2021)). However, the FDA currently does not have the authority to recommend specific allocations, such as prioritizing sales of children's cancer medications to children's cancer hospitals. Thus, for government-driven allocations to be a possible lever to counteract stockpiling, the FDA would need this authority. Alternatively, drug distributors could themselves use allocation mechanisms to apportion essential medicines according to true patient demand. However, there are currently no requirements for drug manufacturers to allocate supplies fairly, even during shortages. Consequently, manufacturers rarely place limits on orders until severe shortages occur. When they do, these allocations are often based on prior sales quantities, such as a percentage of past orders, or a flat amount regardless of health-system size. These allocation policies are unlikely to reflect the regional demand surges that occur during pandemic outbreaks. Getting drug allocation correct the first time is extremely critical because the Drug Supply Chain Security Act requires providing transaction history, transaction information, and transaction statement of the product whenever there is a transfer of ownership of a pharmaceutical product to a different organization (Drug Supply Chain Security Act 21 U.S.C. §582 (2013)). This act makes the transfer of products between health systems difficult, even if a hospital over-purchased a medication and does not need all of it. Our pharmacist collaborator informs us that it is virtually impossible to send overordered products to another system that may need it more urgently. Hence, the current Drug Supply Chain Security Act should be amended to allow product sharing and transfer between medical providers more readily in the face of shortages or public health emergencies.

Lastly, our results demonstrate that prices of COVID-19 drugs did not increase even in a time of abrupt increases in demand. The policy implications are unclear. On one hand, a lack of price increases ensures affordability of essential medicines during a pandemic. On the other hand, it might worsen shortages during pandemic-driven demand surges because prior literature suggests that price increases around disasters could deter buyers from stockpiling and incentivize suppliers to ramp up production (Chakraborti and Roberts 2020, Beatty et al. 2021, Buccafusco et al. 2021). This is especially true for the U.S. generic drug market where the FDA's recent report and experts identify a lack of profitability and incentives for manufacturers as a root cause of persisting drug shortages for the last decade (Woodcock and Wosinska 2013, Fox et al. 2014, FDA 2019). Our findings suggest that policymakers need to provide financial incentives to facilitate manufacturers increasing production of pandemic-related drugs during times of emergency because we find that price increases did not occur. This may be due in part to recently passed state legislation limiting price gouging and increases in certain states (Conti et al. 2018, National Academy for State Health Policy 2021). Although well-intentioned, this legislation could inadvertently depress incentive to increase quantity during a pandemic. Future research could explore this tradeoff further.

5.4. Limitations and Future Research

Our paper has several limitations. First, our data allows us to provide evidence of drug stockpiling only at an aggregate level. We do not have access to data on drug inventory levels and therefore cannot explain stockpiling patterns across different hospitals or regions. Future research may pursue national data on the supply of drugs at a lower level of aggregation (e.g., state level, individual hospital level). However, we are unaware of any dataset that would allow for such analysis on the entirety of national prescription drug sales. IQVIA NSP is not available at this level of disaggregation. Second, we do not have claims data which prevents us from examining the impact of stockpiling on healthcare costs. Third, we cannot assess psychological rationales for stockpiling. Catillon et al. (2020) suggest that news stories about COVID-19 drugs drove some of the increase. Other drivers, such as differential stockout aversion among buyers (Schweitzer and Cachon 2000), emotional factors like differential anxiety by some purchasers over others (Sterman and Dogan 2015), or lack of transparent supply information (Lee et al. 1997a) could also be major drivers of stockpiling but would require data on the decisions of individual buyers. Future studies with laboratory experiments could test the causes of stockpiling behavior during a national crisis. Finally, our data only covers months through September 2020. Future research could extend the time frame to consider the impact of the second and third surges of COVID-19 (Maragakis 2021).

5.5. Conclusions

The COVID-19 pandemic exposes both the challenges and resiliency of the current drug supply chains (Fox et al. 2020, Schondelmeyer et al. 2020, FiercePharma 2020, U.S. International Trade Commission 2020, The White House 2021). As pharmaceutical supply chains impact public health and have unique characteristics different from other retail industries (Jia and Zhao 2017), it is important that researchers continue to aid efforts to build more resilient global pharmaceutical supply chains and prepare for future crises.

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Online Appendices

Appendix A: Drug Sample Sales Construction

Table 1 Drug Sample Sales Construction

Steps		Sample
	Stage 1: Drug Sample Construction	
Step 1	From the FDA Essential Medicines List (n = 227), we identify drugs that are used in the treatment of COVID-19 patients ("exposure group"). We refer to a drug as products having the same molecule (or active ingredient) and product form (Yurukoglu et al. 2017, Conti and Berndt 2020). To identify drugs on FDA Essential Medicines List that are used in the treatment of COVID-19 patients, we review several sources including the FDA List of Drugs Used for Hospitalized Patients with COVID-19 (FDA 2020a), NIH COVID-19 Treatment Guidelines (NIH 2020). Additional expert review was provided by one of the authors who is a pharmacist and a national expert on drug supply. Exposure group includes drugs in the following drug categories as defined in the FDA Essential Medicines List: analgesics, anti-microbial, anticholinergic secretions, anticoagulants, cardiovascular, gastrointestinal, paralytics, psychiatric, pulmonary, sedatives, steroids, vasopressors. Note that several drugs including hydroxychloroquine, chloroquine, budesonide, and tocilizumab are used in the treatment of COVID-19 patients. However, these drugs are excluded from our sample because they are not listed in the FDA's Essential Medicines List.	Exposure Group: n = 62
Step 2	From the initial exposure group, we separate out 6 drugs that have DEA national production quotas.	Exposure Group: n = 56
Step 3	After classifying the exposure group, we identify drugs in the FDA Essential Medicines List that belong to the same and comparable drug categories as our exposure group but not used in the treatment of COVID-19 patients ("control group"). Control group includes drugs in the following drug categories: analgesics, anesthetic, anti-microbial, anticoagulants, antiemetics, antiseptics, antivirals, cardiovascular, gastrointestinal, psychiatric, pulmonary, steroids.	Control Group: n = 61
	Stage 2: National Sales of Drug Sample	
Step 4	Using the IQVIA National Sales Perspective (NSP) database, we match sample drugs to national monthly sales from January 2018 to September 2020. Three sample drugs in the control group did not match to IQVIA NSP sales data – Nitroglycerin (Inserts/implants, Inhalants), and Amikacin (Lung). They are excluded from our sample.	Exposure Group: n = 56, Control Group: n = 58, Observations = 43,811
Step 5	Based on the NSP channel variable, we exclude sales observations to retail channels and other minor channels (e.g. home health care, food stores) and kept only major channels (Non-federal hospital, federal facilities, clinics, long-term care).	Observations = 14,754

Table 2 Sample Drug List

Group	No	Drug[1]	Product Forms[2]	Drug Category[3]	Shortages[4]
Exposure	1	Albuterol	H	Pulmonary	-
Group	2	Amiodarone	I, O	Antihypertensives / Cardiovascular	-
	3	Atropine	I	Antihypertensives / Cardiovascular	July 20'
	4	Azithromycin	I, O	Anti-Microbial	April 20' (O)
	5	Cefepime	I	Anti-Microbial	Y
	6	Cisatracurium	I	Paralytics	April 20'
	7	Dexamethasone	I, O	Steroids	Y (I)
	8	Dexmedetomidine	I	Sedatives	April 20'
	9	Doxycycline	I, O	Anti-Microbial	-
	10	Enoxaparin	I	Anticoagulants	-
	11	Epinephrine	I	Vasopressors	Y
	12	Etomidate	I	Sedatives	April 20'
	13	Famotidine	I, O	Gastrointestinal Agents	May 20' (I, O)
	14	Fluconazole	I, O	Anti-Microbial	-
	15	Furosemide	I, O	Antihypertensives / Cardiovascular	April 20' (I)
	16	Glycopyrrolate	I	Anticholinergic Secretions	-
	17	Haloperidol	I, O	Psychiatric Agents	-
	18	Heparin	I	Anticoagulants	Y
	19	Hydrochlorothiazide	O	Antihypertensives / Cardiovascular	-
	20	Hydrocortisone	I	Steroids	-
	21	Ketamine	I	Sedatives	Y
	22	Levofloxacin	I, O	Anti-Microbial	-
	23	Linezolid	I, O	Anti-Microbial	-
	24	Lorazepam	I, O	Sedatives	Y (I)
	25	Meropenem	I	Anti-Microbial	-
	26	Methylprednisolone	I, O	Steroids	-
	27	Metronidazole	I, O	Anti-Microbial	Y (I)
	28	Midazolam	I, O	Sedatives	April 20' (I)
	29	Norepinephrine	I	Vasopressors	-
	30	Olanzapine	I, O	Psychiatric Agents	-
	31	Pantoprazole	I, O	Gastrointestinal Agents	Y (I)
	32	Phenylephrine	I	Vasopressors	-
	33	Piperacillin/Tazobactam	I	Anti-Microbial	-
	34	Propofol	I	Sedatives	April 20'
	35	Rocuronium	I	Paralytics	-
	36	Succinylcholine	I	Paralytics	-
	37	Vancomycin	I, O	Anti-Microbial	-
	38	Vasopressin	I	Vasopressors	-
	39	Vecuronium	I	Paralytics	May 20'
	Exposure Group (n = 56)				
Control	1	Acyclovir	I, O	Antivirals	-
Group	2	Adenosine	I	Antihypertensives / Cardiovascular	-
	3	Alteplase	I	Anticoagulants / Antiplatelet	-
	4	Amikacin	I	Anti-Microbial	-
	5	Amlodipine	O	Antihypertensives / Cardiovascular	-
	6	Amphotericin B	I	Anti-Microbial	-
	7	Ampicillin	I, O	Anti-Microbial	-
	8	Apixaban	O	Anticoagulants / Antiplatelet	-
	9	Argatroban	I	Anticoagulants / Antiplatelet	-
	10	Benztropine	I, O	Psychiatric Agents	-
	11	Ceftazidime	I	Anti-Microbial	Y
	12	Ceftriaxone	I	Anti-Microbial	-
	13	Chlorhexidine	M, O	Antiseptics	-
	14	Clindamycin	I, O	Anti-Microbial	-
	15	Codeine	O	Analgesics	-
	16	Daptomycin	I	Anti-Microbial	-
	17	Darunavir/cobicistat	O	Antivirals	-
	18	Diltiazem	I, O	Antihypertensives / Cardiovascular	Y (I, O)
	19	Dobutamine	I	Antihypertensives / Cardiovascular	Y
	20	Esmolol	I	Antihypertensives / Cardiovascular	-
	21	Foscarnet	I	Antivirals	-
	22	Hydralazine	I, O	Antihypertensives / Cardiovascular	Sep 20' (I)
	23	Hydrocortisone	O	Steroids	April 20'
	24	Ipratropium	H, N	Pulmonary	-
	25	Isoflurane	H	Anesthetic	-
	26	Labetalol	I, O	Antihypertensives / Cardiovascular	Y (I)
	27	Lactulose	O	Gastrointestinal Agents	-
	28	Loperamide	O	Gastrointestinal Agents	-
	29	Metoprolol	I, O	Antihypertensives / Cardiovascular	Y (I, O)
	30	Micafungin	I	Anti-Microbial	-
	31	Nitroglycerin	I, O	Antihypertensives / Cardiovascular	-
	32	Nitroprusside	I	Antihypertensives / Cardiovascular	-
	33	Ondansetron	I, O	Antiemetics	Y (I)
	34	Oseltamivir	O	Antivirals	-
	35	Penicillin G	I, O	Anti-Microbial	-
	36	Peramivir	I	Antivirals	-
	37	Phenoxybenzamine	O	Antihypertensives / Cardiovascular	-
	38	Protamine	I	Anticoagulants / Antiplatelet	-
	39	Rifampin	I, O	Anti-Microbial	-
	40	Ticagrelor	O	Anticoagulants / Antiplatelet	-
	41	Trimethoprim/Sulfamethoxazole	O	Anti-Microbial	-
	42	Valganciclovir	O	Antivirals	-
	43	Voriconazole	I, O	Anti-Microbial	-
	Control Group (n = 58)				

[1]Drug is defined as products having the same molecule (or active ingredient) and product form (Yurukoglu et al. 2017, Conti and Berndt 2020). [2]*Source*: IQVIA NSP database. [3]Drug categories are defined as the classification used in the FDA Essential Medicines List. [4]We identify the list of drugs that experienced shortages during the pandemic, *Source*: FDA drug shortages database (FDA 2020b).
Abbreviations: (Product Forms) I = Injectables, O = Orals, H = Inhalers, N = Nasal, M = Mouth. (Shortages) Y = Shortages began before the pandemic, April 20' = Shortages began in April 2020, May 20' = Shortages began in May 2020', Sep 20' = Shortages began in September 2020.

Appendix B: Descriptive Statistics

Table 3 presents the descriptive statistics for the continuous variables, stratified by drug group (control, exposure) and the period (pre-COVID, post-COVID). For the outcome variables, geometric means and geometric standard deviations are reported because of the highly right-skewed distributions and to reduce the effect of very large values. The monthly descriptive statistics for outcome variables from March to September of 2020 are also presented. Table 4 reports the correlations between all continuous variables included in the regression analyses.

Table 3 Summary Statistics of Continuous Variables

	Control Group				Exposure Group			
	Pre-COVID		Post-COVID		Pre-COVID		Post-COVID	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
UnitsSold[a]	116,477.3	19.5	102,219.0	20.4	274,203.0	17.2	287,914.8	16.3
March	139,970.1	19.4	141,216.3	23.7	349,780.3	16.5	472,044.2	15.7
April	103,807.5	19.6	82,596.2	20.5	257,286.3	16.9	313,491.9	13.8
May	103,584.3	19.6	82,246.1	19.8	243,006.4	18.0	207,236.6	16.0
June	135,688.5	17.8	109,066.6	19.6	304,753.4	17.2	271,474.4	17.7
July	106,385.2	19.3	92,584.2	19.6	253,471.0	17.2	247,025.4	17.5
August	104,256.6	20.3	92,943.6	20.9	255,593.9	17.1	247,480.7	17.1
September	132,146.3	20.3	127,867.1	19.0	334,097.2	15.6	322,167.6	15.6
SalesAmount[a]	146,287.0	10.8	125,703.2	10.8	226,777.6	10.8	237,066.3	10.6
March	177,727.4	10.8	174,306.9	12.4	282,268.4	10.8	393,772.3	10.5
April	134,068.3	10.5	102,912.5	11.3	214,286.8	10.8	269,047.1	9.9
May	126,806.2	10.8	99,254.6	10.1	204,664.4	11.1	171,030.4	10.3
June	170,775.3	9.8	132,173.9	10.6	259,680.3	10.7	225,292.2	11.2
July	133,248.6	10.5	115,863.9	10.1	209,892.7	10.8	197,289.2	11.1
August	130,358.3	11.0	116,546.3	10.8	215,910.9	10.3	203,107.5	10.6
September	170,209.3	10.9	154,461.6	10.0	278,859.1	9.9	257,139.3	9.8
Price[a]	2.0	9.6	2.0	9.0	1.9	8.1	1.9	8.1
March	2.0	9.9	2.0	9.1	1.9	8.2	1.9	8.4
April	2.0	9.8	2.0	9.5	1.9	8.1	1.9	7.9
May	1.9	9.7	1.9	9.2	1.9	8.2	1.9	8.4
June	2.0	9.5	1.9	9.0	1.9	8.0	1.9	8.3
July	2.0	9.5	2.0	8.8	1.9	8.2	1.8	8.0
August	2.0	9.7	2.0	8.7	1.9	8.3	1.8	7.9
September	2.1	9.3	1.9	8.7	1.9	8.1	1.9	8.0
No. of Producers	5.7	5.0	5.9	5.0	6.5	5.0	7.0	4.9
No. of Prod. Variety	13.1	17.3	13.2	17.5	15.2	16.7	15.8	16.2
Observations	5,836		1,562		5,790		1,566	

Notes. $N = 14{,}754$. [a] Because the distribution of these variables follow log-normal, geometric mean and geometric standard deviation are reported. *Data Source*: IQVIA NSP database.

Table 4 Correlations between Continuous Variables

Variable	1	2	3	4	5
1. *UnitsSold*	1				
2. *SalesAmount*	0.22*	1			
3. *Price*	-0.05*	0.20*	1		
4. *No. of Producers*	0.06*	-0.07*	-0.14*	1	
5. *No. of Prod. Variety*	0.14*	-0.01	-0.13*	0.81*	1

Notes. N = 14,754. $^{*}p < 0.05$.

Appendix C: Test of Pre-period Parallel Trends and Movements

To test the parallel trends in pre-period outcomes between the control group and the exposure group, we use the following regression model:

$$Y_{icmy} = \alpha_i + \gamma_1 Trend_{my} + \gamma_2 Exposure_i \times Trend_{my} + \delta X_{icmy} + \lambda Month_m + \theta Channel_c + \varepsilon_{icmy}, \quad \text{(OA.1)}$$

where Y_{icmy} denotes the outcome variables including $\ln UnitsSold_{icmy}$, $\ln SalesAmount_{icmy}$, and $\ln Price_{icmy}$, for drug i, channel c, month m, and year y; α_i is drug fixed effects; $Exposure_i$ is an indicator variable that takes the value 1 if the drug i belongs to the exposure group; $Trend_{my}$ is the linear time variable in months from January 2018 to February 2020, ranging from 1 to 26, and γ_1 explains the linear time trend in outcomes during the pre-period; the coefficient on the interaction term $Exposure_i \times Trend_{my}$, γ_2 measures the difference in the trend between the exposure group and the control group. We test the parallel trends by testing whether γ_2 is significantly different from 0. X_{icmy} includes each drug's number of product varieties, and the number of producers; $Month_m$ is a vector of month indicators; λ represents monthly seasonality; $Channel_c$ is a vector of channel indicators; θ represents channel effects; and ε_{icmy} is the idiosyncratic error that is not captured.

Table 5 Parallel Trends Test Results

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	$\ln UnitsSold$	$\ln SalesAmount$	$\ln Price$	$UnitsSold$	$SalesAmount$	$Price$
$Trend$	0.000	-0.001	0.000	10,418	8,497	-0.139^{+}
	(0.002)	(0.003)	(0.002)	(16,615)	(11,609)	(0.080)
$Exposure \times Trend$	-0.002	-0.003	-0.002	46,664	-8,901	-0.388
	(0.003)	(0.003)	(0.002)	(51,077)	(12,838)	(0.325)
No. of Producers	0.118*	0.084	-0.006	-1,511,700	-268,822	-0.037
	(0.060)	(0.054)	(0.015)	(1,161,487)	(86,357)	(0.115)
No. of Prod. Variety	0.009	0.007	0.006	841,512	45,496	0.259
	(0.014)	(0.013)	(0.004)	(757,614)	(31,043)	(0.174)
Month effects			Yes			
Channel effects			Yes			
Model			Fixed Effects			
No. of drugs (exposure group)			56			
No. of drugs (control group)			58			
Observations			11,626			

Notes. The time range for the analyses is from January 2018 to February 2020. Columns (1)-(6) use fixed effects estimation at the drug level. Robust standard errors clustered at the drug level are presented in parentheses. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 5 presents the results of the pre-period parallel trend tests. Although they are not included in the main regression analyses, we also test the parallel trends for the untransformed outcome variables. The results for these variables are presented in columns (4)-(6) of Table C1. Based on the analyses, we fail to reject the null hypothesis that the slope of linear time trend between the groups, γ_2, significantly differs from 0 for each variable ($p > 0.1$).

Appendix D: Interpretation of the Difference-in-Differences Coefficients

In this section, we discuss the interpretation of the log-linear difference-in-differences estimates. For the ease of exposition, consider the simplest population difference-in-differences setting,

$$\ln y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Exposure_i + \beta_3 Exposure_i \times Post_t + \varepsilon_{it}, \tag{OA.2}$$

where the variables are defined as in Model 1 with subscript t representing month-year, and $\mathrm{E}[\varepsilon_{it}|Post_t, Exposure_i] = 0$.

Let $y_{0,0} = y_{[Exposure=0,Post=0]}, y_{0,1} = y_{[Exposure=0,Post=1]}, y_{1,0} = y_{[Exposure=1,Post=0]}$, and $y_{1,1} = y_{[Exposure=1,Post=1]}$, where y is the outcome variable in Equation OA.2 in the original scale, or not log-transformed. With the log-transformed outcomes and estimating the parameter β_1, we get, $\beta_1 = E[\ln y_{0,1}] - E[\ln y_{0,0}]$. Because our estimates are relatively large, we cannot directly interpret the coefficient as a % change in y (Stock and Watson 2012). To get the precise interpretation, by exponentiating, we have $e^{\beta_1} = e^{(E[\ln y_{0,1}] - E[\ln y_{0,0}])} = \frac{e^{E[\ln y_{0,1}]}}{e^{E[\ln y_{0,0}]}} = \frac{G(y_{0,1})}{G(y_{0,0})}$, where $G(\cdot)$ is the geometric mean function. Hence, we can calculate the ratio between the geometric mean of pre-period outcome and post-period outcome for the control group using β_1.

Next, for the difference-in-differences parameter, β_3, we have $\beta_3 = (E[\ln y_{1,1}] - E[\ln y_{1,0}]) - (E[\ln y_{0,1}] - E[\ln y_{0,0}])$, and by exponentiating, we get, $e^{\beta_3} = e^{(E[\ln y_{1,1}] - E[\ln y_{1,0}]) - (E[\ln y_{0,1}] - E[\ln y_{0,0}])} = \frac{e^{(E[\ln y_{1,1}] - E[\ln y_{1,0}])}}{e^{(E[\ln y_{0,1}] - E[\ln y_{0,0}])}} = \frac{\frac{G(y_{1,1})}{G(y_{1,0})}}{\frac{G(y_{0,1})}{G(y_{0,0})}}$. What we have is the ratio between the ratio of two outcomes (pre- and post-) for the exposure group and the ratio of two outcomes (pre- and post-) for the control group. Since $e^{\beta_1} = \frac{G(y_{0,1})}{G(y_{0,0})}$, we can calculate back $\frac{G(y_{1,1})}{G(y_{1,0})}$, the ratio of pre- and post- outcomes for the exposure group, by $e^{(\beta_3 + \beta_1)}$. Finally, because we are interested in the amount of drug sales related to COVID-19 treatments — the difference between the total sales of the exposure group, $y_{1,1}$, and the portion of drug sales of the exposure group not related to COVID-19 treatments estimated by the change in sales of the control group — we take the difference of ratios between the groups, $\frac{G(y_{1,1})}{G(y_{1,0})} - \frac{G(y_{0,1})}{G(y_{0,0})}$. This can be calculated using our parameters, $e^{(\beta_3 + \beta_1)} - e^{\beta_1}$. Note that this ratio difference is the % of drug sales related to COVID-19 treatments during the post-period for the exposure group relative to the pre-period average monthly sales amount of the exposure group. The assumption here is that the portion of non-COVID-19 related sales follow parallel movement between the exposure and control groups during the post-period.

Appendix E: Analyses with Extended Sample

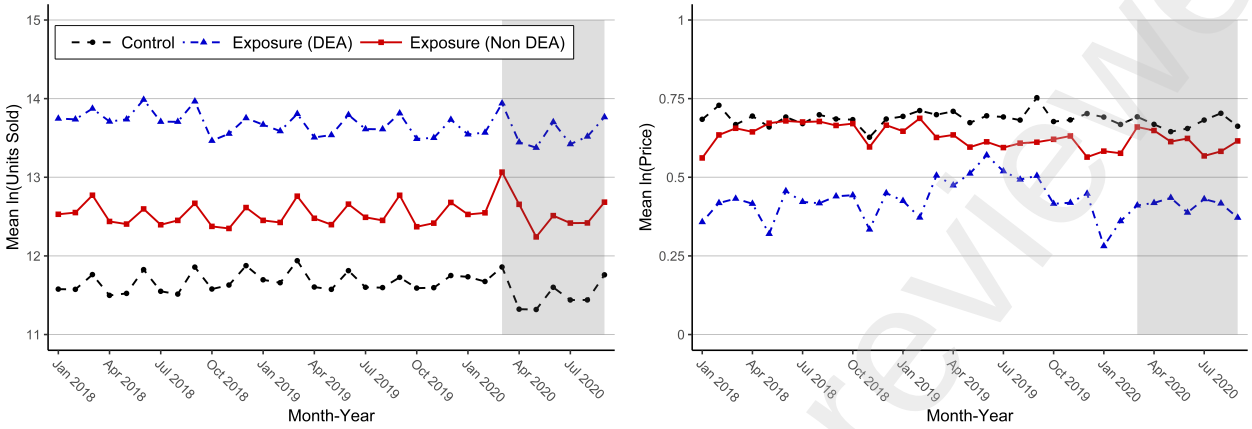
Table 6 Analyses Results with All Channels

Outcome Variable	ln *UnitsSold*		ln *Price*	
Explanatory Variable	(1)	(2)	(3)	(4)
Post	-0.078^{+}	-	-0.001	-
	(0.045)		(0.025)	
March 2020		0.069		-0.016
		(0.048)		(0.027)
April 2020		-0.154**		0.021
		(0.059)		(0.029)
May 2020		-0.193***		0.007
		(0.055)		(0.030)
June 2020		-0.100^{+}		0.015
		(0.053)		(0.031)
July 2020		-0.065		0.007
		(0.055)		(0.033)
August 2020		-0.070		-0.008
		(0.058)		(0.035)
September 2020		-0.032		-0.039
		(0.057)		(0.036)
Exposure × *Post*	0.053	-	-0.014	-
	(0.080)		(0.042)	
Exposure × *March* 2020		0.108		0.007
		(0.080)		(0.040)
Exposure × *April* 2020		0.316**		-0.004
		(0.112)		(0.043)
Exposure × *May* 2020		0.042		-0.014
		(0.094)		(0.044)
Exposure × *June* 2020		-0.017		-0.040
		(0.093)		(0.053)
Exposure × *July* 2020		-0.015		-0.034
		(0.089)		(0.052)
Exposure × *August* 2020		-0.001		-0.029
		(0.091)		(0.051)
Exposure × *September* 2020		-0.081		0.015
		(0.090)		(0.053)
Number of Producers	0.255***	0.255***	0.021	0.021
	(0.046)	(0.046)	(0.016)	(0.016)
Number of Prod. Variety	0.041***	0.041***	0.018***	0.018***
	(0.012)	(0.012)	(0.004)	(0.004)
Month effects	Yes		Yes	
Channel effects	Yes		Yes	
Drug category × time trends	Yes		Yes	
Adjusted R^2	0.574	0.574	0.094	0.094
No. of drugs (exposure group)	56		56	
No. of drugs (control group)	58		58	
Observations	43,811		43,811	

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Appendix F: Analysis of Drugs with Production Quotas

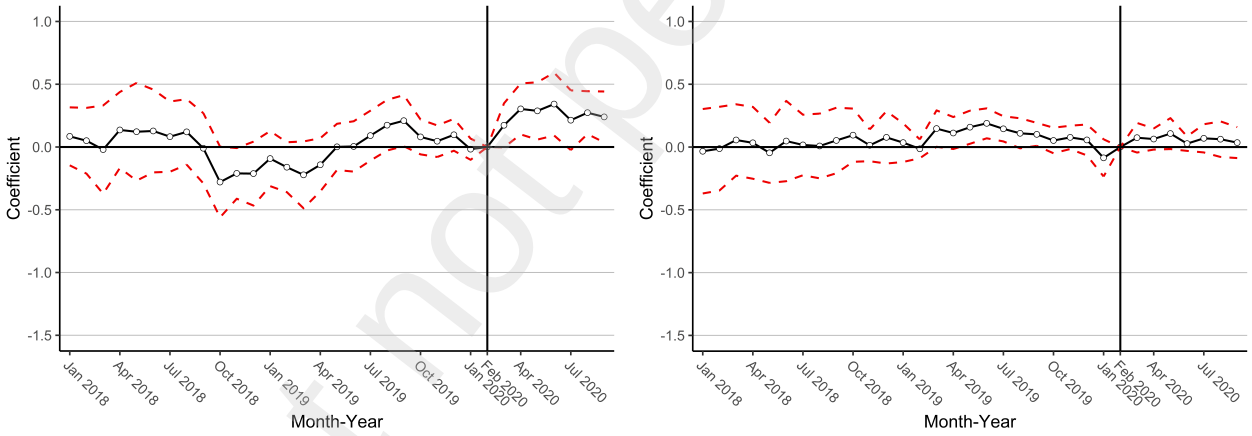
Figure 1 ln UnitsSold and ln Price by DEA-Controlled and Non-DEA-Controlled Exposure Groups



(a) ln *UnitsSold* (b) ln *Price*

Notes. Panels (a) and (b) plot the unadjusted mean of log transformed *UnitsSold* and *Price* by groups, respectively. The grey shaded area represents the COVID-19 pandemic period. *Source*: IQVIA NSP.

Figure 2 Dynamics of Difference-in-Differences Estimates for Entire Period (DEA-Controlled Exposure Group)



(a) ln *UnitsSold* (b) ln *Price*

Notes. Panels (a) and (b) plot the difference-in-differences coefficients (points connected with a solid line) for each month of the entire period for DEA-controlled exposure group, for the outcome variable ln *UnitsSold* and ln *Price*, respectively. Specifically, the outcome variable is regressed onto the month effects, the channel effects, drug fixed effects, control variables, and interactions of the exposure indicator with a set of indicator variables corresponding to each month with the baseline month, February 2020 (the month just before the pandemic, shown by the vertical lines). The 95% confidence interval, calculated with robust clustered standard errors, is plotted with dashed red lines.

Table 7 Analyses of Changes in Sales Volume and Price of DEA-Controlled Exposure Group Drugs During the Early Stages of the Pandemic

Outcome Variable	ln *UnitsSold*		ln *Price*	
Explanatory Variable	(1)	(2)	(3)	(4)
Post	-0.170***	-	-0.030	-
	(0.031)		(0.021)	
March 2020		0.037		-0.039
		(0.059)		(0.026)
April 2020		-0.255***		-0.018
		(0.062)		(0.021)
May 2020		-0.322***		-0.030
		(0.052)		(0.033)
June 2020		-0.238***		-0.030
		(0.043)		(0.023)
July 2020		-0.177***		-0.015
		(0.047)		(0.028)
August 2020		-0.138*		-0.027
		(0.060)		(0.025)
September 2020		-0.103+		-0.051+
		(0.057)		(0.030)
Exposure × *Post*	0.323***	-	-0.022	-
	(0.085)		(0.054)	
Exposure × *March* 2020		0.223*		-0.006
		(0.110)		(0.056)
Exposure × *April* 2020		0.358***		-0.018
		(0.098)		(0.048)
Exposure × *May* 2020		0.346***		0.022
		(0.090)		(0.061)
Exposure × *June* 2020		0.404***		-0.059+
		(0.109)		(0.032)
Exposure × *July* 2020		0.281**		-0.021
		(0.105)		(0.067)
Exposure × *August* 2020		0.345***		-0.029
		(0.093)		(0.084)
Exposure × *September* 2020		0.315**		-0.059
		(0.106)		(0.085)
Number of Producers	0.176*	0.176*	-0.022	-0.022
	(0.079)	(0.079)	(0.018)	(0.018)
Number of Prod. Variety	-0.009	-0.009	0.011***	0.011***
	(0.014)	(0.014)	(0.003)	(0.003)
Month effects	Yes		Yes	
Channel effects	Yes		Yes	
Drug category × time trends	Yes		Yes	
Adjusted R^2	0.503	0.503	0.106	0.105
No. of drugs (exposure group)	6		6	
No. of drugs (control group)	58		58	
Observations	8,190		8,190	

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Appendix G: Robustness Checks

G.1. Sensitivity Analyses

Table 8 Sensitivity Analyses for Model (1) (Outcome Variable: $\ln UnitsSold$)

Outcome Variable	$\ln UnitsSold$					
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.131***	-0.159***	-0.167***	-0.132+	-0.158***	-0.154***
	(0.037)	(0.031)	(0.032)	(0.080)	(0.033)	(0.033)
Exposure × *Post*	0.173***	0.207***	0.174***	0.029	0.175**	0.166*
	(0.050)	(0.055)	(0.050)	(0.133)	(0.065)	(0.066)
Number of Producers				0.470***	0.121*	0.123*
				(0.072)	(0.056)	(0.056)
Number of Prod. Variety				0.042*	0.011	0.011
				(0.021)	(0.014)	(0.014)
$\ln(COVID\ hospitalizations_{t+1}+1)$					-0.003	-0.003
					(0.004)	(0.004)
Price						0.002+
						(0.001)
Month effects	No	Yes	Yes	Yes	Yes	Yes
Channel effects	Yes	Yes	Yes	No	Yes	Yes
Drug category × time trends	Yes	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.515	0.519	0.520	0.234	0.530	0.530
No. of drugs (exposure group)				56		
No. of drugs (exposure group)				58		
Observations				14,754		

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Table 9 Sensitivity Analyses for Model (2) (Outcome Variable: $\ln UnitsSold$**)**

Outcome Variable	$\ln UnitsSold$					
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
March 2020	0.260***	0.039	0.030	-0.019	0.019	0.022
	(0.057)	(0.059)	(0.060)	(0.086)	(0.058)	(0.059)
April 2020	-0.358***	-0.265***	-0.273***	-0.228*	-0.259***	-0.258***
	(0.057)	(0.058)	(0.059)	(0.090)	(0.056)	(0.056)
May 2020	-0.431***	-0.317***	-0.324***	-0.247***	-0.307***	-0.303***
	(0.077)	(0.063)	(0.063)	(0.086)	(0.054)	(0.054)
June 2020	-0.085	-0.209***	-0.214***	-0.160+	-0.201***	-0.198***
	(0.072)	(0.051)	(0.052)	(0.084)	(0.047)	(0.046)
July 2020	-0.243***	-0.157***	-0.163***	-0.149	-0.160***	-0.157***
	(0.055)	(0.047)	(0.044)	(0.094)	(0.047)	(0.046)
August 2020	-0.206***	-0.117*	-0.122**	-0.099	-0.115*	-0.110*
	(0.039)	(0.051)	(0.047)	(0.102)	(0.053)	(0.053)
September 2020	0.082+	-0.094*	-0.098*	-0.012	-0.077	-0.072
	(0.044)	(0.043)	(0.047)	(0.098)	(0.051)	(0.050)
$Exposure \times March$ 2020	0.273***	0.303***	0.272***	0.178	0.298***	0.289***
	(0.081)	(0.081)	(0.081)	(0.130)	(0.070)	(0.073)
$Exposure \times April$ 2020	0.048***	0.513***	0.480***	0.302*	0.483***	0.483***
	(0.097)	(0.104)	(0.097)	(0.145)	(0.102)	(0.102)
$Exposure \times May$ 2020	0.137	0.172+	0.137	0.040	0.164+	0.155
	(0.086)	(0.092)	(0.086)	(0.133)	(0.099)	(0.100)
$Exposure \times June$ 2020	0.059	0.097	0.059	-0.073	0.079	0.068
	(0.082)	(0.084)	(0.082)	(0.140)	(0.093)	(0.092)
$Exposure \times July$ 2020	0.118+	0.157*	0.118+	-0.016	0.134	0.128
	(0.069)	(0.074)	(0.069)	(0.152)	(0.087)	(0.087)
$Exposure \times August$ 2020	0.084	0.124*	0.083	-0.076	0.091	0.083
	(0.056)	(0.057)	(0.056)	(0.155)	(0.060)	(0.061)
$Exposure \times September$ 2020	0.048	0.090+	0.048	-0.176	0.040	0.025
	(0.053)	(0.053)	(0.053)	(0.157)	(0.068)	(0.069)
Number of Producers				0.470***	0.121*	0.122*
				(0.072)	(0.056)	(0.056)
Number of Prod. Variety				0.042*	0.011	0.011
				(0.021)	(0.014)	(0.014)
$\ln(COVID\ hospitalizations_{t+1}+1)$					-0.004	-0.004
					(0.004)	(0.004)
Price						0.002+
						(0.001)
Month effects	No	Yes	Yes	Yes	Yes	Yes
Channel effects	Yes	Yes	Yes	No	Yes	Yes
Drug category × time trends	Yes	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.518	0.520	0.520	0.234	0.530	0.531
No. of drugs (exposure group)				56		
No. of drugs (exposure group)				58		
Observations				14,754		

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Table 10 Sensitivity Analyses for Model (1) (Outcome Variable: $\ln Price$**)**

Outcome Variable	$\ln Price$				
Explanatory Variable	(1)	(2)	(3)	(4)	(5)
Post	0.003	-0.025	-0.002	-0.001	-0.002
	(0.023)	(0.026)	(0.024)	(0.025)	(0.024)
Exposure × *Post*	-0.008	-0.002	-0.008	-0.014	-0.010
	(0.040)	(0.046)	(0.040)	(0.041)	(0.041)
Number of Producers				-0.004	-0.015
				(0.014)	(0.015)
Number of Prod. Variety				0.011**	0.008*
				(0.004)	(0.004)
Month effects	No	Yes	Yes	Yes	Yes
Channel effects	Yes	Yes	Yes	No	Yes
Drug category × time trends	Yes	No	Yes	Yes	Yes
Adjusted R^2	0.040	0.020	0.040	0.037	0.037
No. of drugs (exposure group)			56		
No. of drugs (exposure group)			58		
Observations			14,754		

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 11 Sensitivity Analyses for Model (2) (Outcome Variable: $\ln Price$**)**

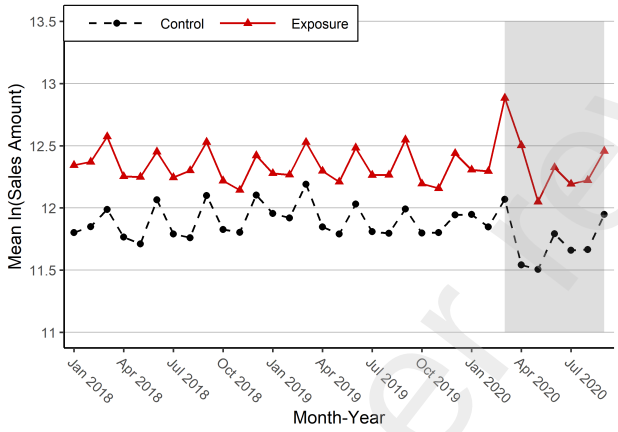
Outcome Variable			$\ln Price$		
Explanatory Variable	(1)	(2)	(3)	(4)	(5)
March 2020	-0.017	-0.035	-0.014	-0.017	-0.016
	(0.027)	(0.032)	(0.027)	(0.027)	(0.027)
April 2020	0.007	-0.016	0.006	0.008	0.006
	(0.025)	(0.028)	(0.025)	(0.026)	(0.025)
May 2020	-0.021	-0.031	-0.008	-0.004	-0.007
	(0.027)	(0.031)	(0.031)	(0.032)	(0.031)
June 2020	0.012	-0.017	0.004	0.007	0.004
	(0.024)	(0.026)	(0.025)	(0.026)	(0.026)
July 2020	0.020	-0.006	0.018	0.020	0.018
	(0.026)	(0.029)	(0.029)	(0.029)	(0.029)
August 2020	0.018	-0.020	0.004	0.006	0.004
	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)
September 2020	-0.006	-0.048	-0.023	-0.020	-0.024
	(0.030)	(0.031)	(0.031)	(0.032)	(0.032)
Exposure × *March* 2020	0.051	0.055	0.051	0.049	0.051
	(0.044)	(0.053)	(0.044)	(0.044)	(0.044)
Exposure × *April* 2020	0.017	0.021	0.017	0.009	0.014
	(0.042)	(0.043)	(0.042)	(0.044)	(0.044)
Exposure × *May* 2020	0.010	0.016	0.010	0.005	0.008
	(0.052)	(0.059)	(0.052)	(0.052)	(0.052)
Exposure × *June* 2020	-0.012	-0.007	-0.012	-0.019	-0.015
	(0.049)	(0.057)	(0.049)	(0.050)	(0.049)
Exposure × *July* 2020	-0.074	-0.066	-0.074	-0.081	-0.077
	(0.051)	(0.053)	(0.051)	(0.052)	(0.052)
Exposure × *August* 2020	-0.056	-0.048	-0.056	-0.065	-0.060
	(0.051)	(0.054)	(0.051)	(0.052)	(0.051)
Exposure × *September* 2020	0.006	0.015	0.006	-0.003	0.004
	(0.051)	(0.054)	(0.051)	(0.053)	(0.052)
Number of Producers				-0.004	-0.015
				(0.032)	(0.015)
Number of Prod. Variety				0.011**	0.009*
				(0.004)	(0.004)
Month effects	No	Yes	Yes	Yes	Yes
Channel effects	Yes	Yes	Yes	No	Yes
Drug category × time trends	Yes	No	Yes	Yes	Yes
Adjusted R^2	0.039	0.020	0.040	0.025	0.043
No. of drugs (exposure group)			56		
No. of drugs (exposure group)			58		
Observations			14,754		

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

G.2. Analyses with Another Outcome Variable

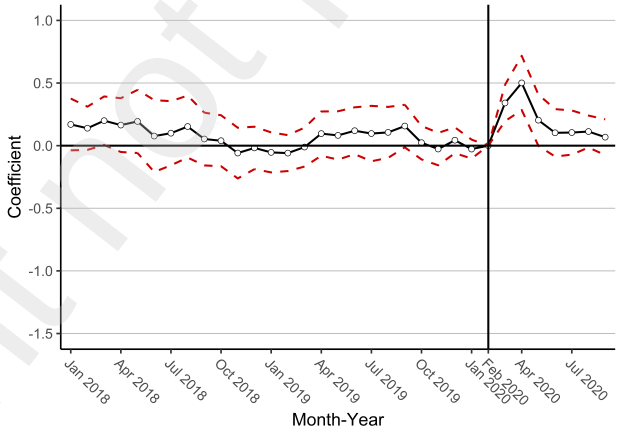
In this section, we analyze Models (1) and (2) with an outcome variable, *SalesAmount*, which is the total amount of sale of a drug to a channel in a month measured in U.S. dollars, as a robustness check of our main results. The below Figure 3 plots the unadjusted mean of log-transformed *SalesAmount* by groups, and the Figure 4 shows the test results of pre-period parallel movement of ln *SalesAmount* between the groups.

Figure 3 ln SalesAmount by Group



Notes. The figure plots the unadjusted mean of log transformed *SalesAmount* by group. The grey shaded area represents the COVID-19 pandemic period. *Source*: IQVIA NSP.

Figure 4 Dynamics of Difference-in-Differences Estimates for ln SalesAmount



Notes. The figure plots the difference-in-differences coefficient estimates (points connected with a solid line) for each month of the entire period for the outcome variables ln *SalesAmount*. Specifically, the outcome variable is regressed onto the month effects, the channel effects, drug fixed effects, control variables, and interactions of the exposure indicator with a set of indicator variables corresponding to each month with the baseline month, February 2020 (the month just before the pandemic). The 95% confidence interval calculated with the robust standard errors, clustered at the drug level, is plotted with dashed red lines.

The results of the estimation of Models (1) and (2) are presented in columns (1) and (2) of 12, respectively. Similar to our main analyses with *UnitsSold*, the sales amount of drugs related to non-COVID care decreased significantly during the post-period ($\beta_1 = -0.145, p < 0.001$, 13.5% decrease relative to pre-period average monthly sales), whereas the sales amount of the exposure group increased significantly ($\beta_2 = 0.145, p < 0.05$),

indicating about 13.5% of pre-period mean monthly sales amount of the exposure group were sold for COVID-19 treatments in each post-period month, on average. Also, the sales amount related to COVID-19 were concentrated during the first two months ($\beta_{March\ 2020} = 0.295, p < 0.01$; $\beta_{April\ 2020} = 0.455, p < 0.001$), but were not significantly associated with months after April. The results here are consistent with the main results of the paper in Table 1 and suggest stockpiling patterns in the early months of the pandemic.

Table 12 Analyses of Changes in Sales Amounts During the Early Stages of the Pandemic

Outcome Variable	$\ln SalesAmount$	
Explanatory Variable	(1)	(2)
Post	-0.145***	-
	(0.043)	
March 2020		0.024
		(0.071)
April 2020		-0.223***
		(0.067)
May 2020		-0.290***
		(0.058)
June 2020		-0.188***
		(0.053)
July 2020		-0.125*
		(0.058)
$August 2020		-0.106+
		(0.055)
September 2020		-0.096+
		(0.056)
Exposure × *Post*	0.145*	-
	(0.067)	
Exposure × *March* 2020		0.295**
		(0.090)
Exposure × *April* 2020		0.455***
		(0.105)
Exposure × *May* 2020		0.128
		(0.088)
Exposure × *June* 2020		0.031
		(0.086)
Exposure × *July* 2020		0.041
		(0.082)
Exposure × *August* 2020		0.043
		(0.076)
Exposure × *September* 2020		-0.004
		(0.076)
Number of Producers	0.083+	0.082+
	(0.050)	(0.050)
Number of Prod. Variety	0.011	0.011
	(0.012)	(0.012)
Month effects	Yes	
Channel effects	Yes	
Drug category × time trends	Yes	
Adjusted R^2	0.540	0.541
No. of drugs (exposure group)	56	
No. of drugs (exposure group)	58	
Observations	14,754	

Notes. All regressions are estimated with fixed effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

G.3. Specification Test with Random Effects Estimation

Table 13 Difference-in-Differences Models with Random Effects

Outcome Variable	$\ln UnitsSold$		$\ln Price$	
Explanatory Variable	(1)	(2)	(3)	(4)
Exposure	1.239**	1.241**	-0.662	-0.661
	(0.418)	(0.418)	(0.469)	(0.469)
Post	-0.156***	-	-0.002	-
	(0.034)		(0.024)	
March 2020		0.020		-0.016
		(0.059)		(0.027)
April 2020		-0.257***		0.006
		(0.056)		(0.025)
May 2020		-0.304***		-0.007
		(0.053)		(0.031)
June 2020		-0.199***		0.004
		(0.047)		(0.026)
July 2020		-0.157***		0.018
		(0.047)		(0.029)
August 2020		-0.113*		0.004
		(0.055)		(0.030)
September 2020		-0.075		-0.024
		(0.051)		(0.032)
Exposure × *Post*	0.136*	-	-0.010	-
	(0.058)		(0.041)	
Exposure × *March* 2020		0.247**		0.051
		(0.080)		(0.044)
Exposure × *April* 2020		0.431***		0.014
		(0.094)		(0.044)
Exposure × *May* 2020		0.114		0.008
		(0.080)		(0.052)
Exposure × *June* 2020		0.027		-0.015
		(0.080)		(0.049)
Exposure × *July* 2020		0.082		-0.077
		(0.075)		(0.052)
Exposure × *August* 2020		0.041		-0.060
		(0.072)		(0.051)
Exposure × *September* 2020		-0.011		0.005
		(0.069)		(0.052)
Number of Producers	0.123*	0.123*	-0.015	-0.015
	(0.054)	(0.054)	(0.014)	(0.014)
Number of Prod. Variety	0.012	0.012	0.008*	0.008*
	(0.014)	(0.014)	(0.004)	(0.004)
Month effects	Yes		Yes	
Channel effects	Yes		Yes	
Drug category × time trends	Yes		Yes	
No. of drugs (exposure group)	56		56	
No. of drugs (exposure group)	58		58	
Observations	14,754		14,754	

Notes. All regressions are estimated with random effects at the drug level. Robust standard errors clustered at the drug level are reported in parentheses. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

G.4. Product-Channel-Month-Year Level Analyses

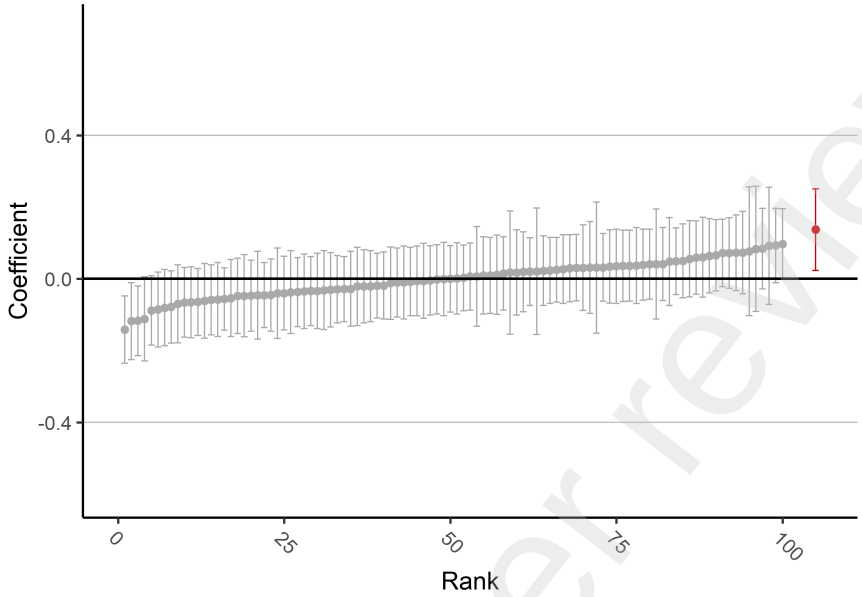
Table 14 Product-Channel-Month-Year Level Analyses Results

Outcome Variable	$\ln UnitsSold$		$\ln SalesAmount$		$\ln Price$	
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.003	-	-0.010	-	-0.006	-
	(0.028)		(0.028)		(0.009)	
March 2020		0.209***		0.213***		0.004
		(0.029)		(0.030)		(0.010)
April 2020		-0.141***		-0.147***		-0.006
		(0.032)		(0.033)		(0.011)
May 2020		-0.153***		-0.167***		-0.013
		(0.032)		(0.033)		(0.012)
June 2020		-0.047		-0.058+		-0.010
		(0.034)		(0.035)		(0.011)
July 2020		-0.014		-0.016		-0.002
		(0.036)		(0.037)		(0.013)
August 2020		0.034		0.034		0.000
		(0.036)		(0.037)		(0.013)
September 2020		0.073*		0.055		-0.018
		(0.037)		(0.038)		(0.013)
Exposure × *Post*	0.060+	-	0.060+	-	0.000	-
	(0.035)		(0.036)		(0.012)	
Exposure × *March* 2020		0.129***		0.153***		0.025+
		(0.039)		(0.040)		(0.013)
Exposure × *April* 2020		0.191***		0.205***		0.014
		(0.042)		(0.044)		(0.015)
Exposure × *May* 2020		-0.001		-0.007		-0.006
		(0.040)		(0.042)		(0.015)
Exposure × *June* 2020		-0.018		-0.030		-0.011
		(0.044)		(0.044)		(0.014)
Exposure × *July* 2020		0.067		0.055		-0.013
		(0.045)		(0.046)		(0.015)
Exposure × *August* 2020		0.040		0.031		-0.009
		(0.045)		(0.047)		(0.016)
Exposure × *September* 2020		-0.002		-0.007		-0.004
		(0.046)		(0.047)		(0.016)
Month effects	Yes		Yes		Yes	
Channel effects	Yes		Yes		Yes	
Drug category × time trends	Yes		Yes		Yes	
Adjusted R^2	0.229	0.230	0.237	0.237	0.010	0.010
No. of drugs (exposure group)	56		56		56	
No. of drugs (exposure group)	58		58		58	
No. of products (exposure group)	1,444		1,444		1,444	
No. of products (exposure group)	1,215		1,215		1,215	
Observations	209,653		209,653		209,653	

Notes. All regressions are estimated with fixed effects at the product level. Robust standard errors clustered at the product level are reported in parentheses. Adjusted within R-squared values are reported. $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

G.5. Placebo Tests

Figure 5 Placebo Tests of the Effect of Pandemic on Drug Units Sold



Notes. Placebo exposure group of 56 drugs were randomly selected and the placebo pandemic months were randomly assigned 100 times. Each point corresponds to an estimation of Model (1) in the paper. The error bars represent the 95% confidence interval calculated using the robust standard errors clustered at the drug. The coefficient and confidence interval for the true data are plotted on the far right (red point and error bars).

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