

# An Empirical Study of the Generic Drug Competition Effect on Pharmaceutical Prices in Mainland China\*

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The fast-growing global pharmaceutical industry has played a pivotal role in health and economic development. Alongside the accumulation of R&Ds, the more affordable generic drug has aroused public attention for its tremendous potential benefits in social welfare. Generic products are of crucial importance in developing countries, but the qualities are concerning. China has the second-largest pharmaceutical industry worldwide and is a major manufacturer of generic drugs. Considering the expanding market size and the high potentials, policymakers in China must thoroughly understand the market features and the factors that affect pharmaceutical prices. This dissertation will provide an empirical analysis of the correlation between the price and the generic competition based on the historical bidding records in China. Using a quasi-hedonic pricing model estimated by a fixed-effect estimator, the paper presents evidence of a negative generic competition effect on pharmaceutical prices at a statistically significant level. Using a difference-in-difference approach in the context of the implementation of the 2016 Drug Consistency Evaluation in China, the study demonstrates that a stringent regulation on generic drug quality will strengthen the competition effect on pharmaceutical prices, mitigate the market distortions and reap the full benefits of competition.

## I. INTRODUCTION

The pharmaceutical industry has undergone a rapid expansion worldwide since the middle of the 20th century and reached 1.27 trillion U.S. dollars in 2020 (Mikulic, 2020). It transformed structurally from producing selected chemicals to a research-oriented sector, further contributing to the improvement of households' health standard and economic development (Caves, Whinston, Hurwitz, Pakes and Temin, 1991; Lichtenberg, 2014). The prosperity of the innovative pharmaceutical market brought forth opportunities for generics and therapeutic alternative manufacturers. The generic drug firms took advantage of the spill-over effects of the R&D, and entered the market with lower prices. The rising generics generated market competition that also exerted pressures on the innovators' market domination position (DiMasi and Paquette, 2004). The trade-offs between promoting innovation and securing competitive market outcomes require comprehensive evaluations, subject to the country's market condition, to optimize social welfare.

The pharmaceutical market in Low- and Medium-Income Countries (LMICs) differs from that in High-Income Countries (HICs) in many ways (Kremer, 2002). Despite the smaller absolute value of households' pharmaceutical expenditure, the proportion of healthcare

spending on pharmaceuticals was about 20-60% in LMICs in comparison to less than 18% in HICs (Cameron, Hill, and Whyte, 2015). One of the key objectives of LMICs is to enhance the affordability of essential drugs, highlighting the importance of generic as a cost-efficient substitute for branded drugs<sup>1</sup>. Economists agreed that substantial savings, on average of 9-89%, could be achieved by switching from originator to its cheaper generics (Cameron, Hill, and Whyte, 2015; Rida and Ibrahim, 2018). However, alongside insufficient insurance coverage and inadequate regulations, many LMICs' markets are "flooded with low-quality generics or even counterfeits" (Wang, 2006).

Among the LMICs, China has been one of the fastest-growing pharmaceutical markets. In recent years, China became the second-largest pharmaceutical industry globally (Wood, 2020) and was predicted to be the largest by 2050 (Zhang and Deng, 2008). China, as a major generic drug manufacturer in the world with 97% of its market consisting of imitations of sophisticated foreign drugs, is necessitated to be studied thoroughly (Chan and Daim, 2011).

China's pharmaceutical market shares some problems of the developing world, including less stringent quality control and a lack of a well-established competition environment (Wang, 2006). Most of the local generic firms in China are small-scale competitors producing low-quality generics of outdated molecules. The potential of the competitive pharmaceutical market in China remains to be high. Economists have foreseen the enormous social benefit of switching from originator to well-regulated generics. According to Intercontinental Medical Statistics (IMS) Health data, a total of US\$1.4 and

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\* I would like to express my deepest appreciation to Dr Anne Brockmeyer and Dr Frank Witte for their consistent assistance, guidance and patience throughout the duration of this module. I would like to extend my sincere thanks to UCL and the Department of Economics for all the unwavering support I have gained over the past three years.

Thanks also to my family and friends for their encouragement and valuable advice.

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<sup>1</sup> In the following paper, the word 'patented drugs' and 'branded drugs' are used interchangeably.

2.8 billion (2014 US\$) could be saved by switching from branded anti-hypertensives and anti-diabetics to generic equivalents respectively (Sun, Ren and Wirtz, 2016). In public hospitals in China, an average of 65%, equivalent to US \$370 million, could be saved by switching only four medicines (Cameron, Mantel-Teeuwisse, Leufkens and Laing, 2012).

The pharmaceutical industry in Mainland China has undergone rounds of transformation, including a series of policies securing the interchangeability of generics and originators by reassessing the quality and efficiency of generics. One of the most remarkable policies is the enforcement of the Drug Consistency Evaluation. It requires the generic manufacturers to provide a comparative study to demonstrate bioequivalence as the branded drugs. Approximately 1,900 pharmaceutical companies and 18,000 generic drugs are expected to participate in the revaluation procedure before 2022 (Huang, Barber, Xu and Cheng, 2017).

Moreover, several rounds of pricing policy reforms have also taken place in the last few decades, including an extensive removal of direct government pricing and reference pricing, which increased the market power in the pricing system with additional flexibility. In Mainland China, the primary distribution channel of pharmaceutical products is the medical institutions which account for about 80% of the pharmaceutical sales (Zhang and Bian, 2007). Since the late 1990s, these medical institutions in China have been purchasing pharmaceutical products through a bidding system governed by the National Medical Products Administration (formerly known as China Food and Drug Administration) under the supervision of the Ministry of Health of the People's Republic of China. All manufacturers and distributors that met the criteria were eligible to participate (Wu, Xu, Liu and Wu, 2014).

Considering its expanding market size and the potential social welfare, it is of crucial importance for the policymakers in China to understand the market features and the factors that affect pharmaceutical prices. This dissertation provides an empirical analysis of the correlation between the price and the generic competition based on the historical bidding records in China. Then, the paper illustrates the critical role of generic drug quality controls in improving the efficiency of market competition and reducing drug prices. The paper will be structured in the following way: Section II covers the literature review; Section III discusses the data, set out the theoretical framework, and identifies the variables and empirical estimators; Section IV summarises the estimation results; and Section V evaluates the findings and limitations of this research. Suggestions on future research and policy implications will also be provided based on the analysis result.

## II. LITERATURE REVIEW

### A. The Literature Gap and the Fundamental Quasi-Hedonic Price Framework

Generic drug competition has not been a popular topic among researchers. Despite the importance of drug affordability in the developing world, most of the studies in this realm targeted at HICs. By 2012, approximately 6.3% of full-text publications on the pharmaceutical industry were related to generic medicine policies. Among those publications, only 25% evaluated policies in LMICs (Kaplan, Ritz, Vitello and Wirtz, 2012). Furthermore, studies focused on China's generic drug competition were even rarer.

A common methodology in analysing the performance of competition and drug prices is by adopting a quasi-hedonic price model. The model is firstly introduced by Danzon and Chao (2000). It is one of the most fundamental cross-country empirical analysis with comprehensive data that simultaneously examines both generic and therapeutic price competition. Focusing on seven selected HICs, the authors hypothesized that price is adversely affected by the number of generic competitors (identical molecules), the number of therapeutic competitors (different molecules with similar effects), and the number of generic competitors in other relevant therapeutic classes, alongside various quality attributes (for example, package size and strength). The authors concluded that the generic drug competition effect on price is significant in unregulated countries and insignificant in highly regulated countries. However, therapeutic competition effects are less conclusive.

Danzon, Mulcahy and French (2015) conducted further research applying the same model on emerging economies through multivariate regression estimation, which exhibited differences in pharmaceutical competition performance across LMICs. They found that the generics were priced on average 32% below originators in the retail channel but with large variance and that generic competition only weakly affects drug prices. In this research, the author distinguished the retail and tendered generic drug markets. The marginal effect of tendering generics on originator prices was significantly negative (-0.068), whereas, in contrast, additional retail generics only tended to lower average retail generic prices but had no effect on originator prices.

The divergence in competition performance among retail and tendered drugs in LMICs gave rise to the debates about generic drug quality. The authors claimed that in HICs with well-regulated generic drug administration processes, the quality of pharmaceutical alternatives was strictly monitored to ensure substitutability. LMICs failed to accomplish this because they did not have stringent requirements on bioequivalent demonstration or did not meet international goods manufacturing practice standards. Sun, Santoro, Meng, Liu and Eggleston (2008) and Yu, Li, Shi and Yu (2010) contributed to

evidence on this, suggesting generic drug quality was not equal across countries. Furthermore, asymmetric information about generic drug quality also undermined price competition efficiency in LMICs.

The quasi-hedonic pricing model suffered from endogeneity issues due to reverse causality. Since price is often associated as an indicator of profit, price level might positively correlate to profit-seeking firms' entry decision. Danzon identified this endogeneity as an upward bias that led to an underestimation of competition effects. He found evidence of this correlation in another paper (Danzon and Furukawa, 2011), showing that generic drug entry into the market was indeed related to market size. However, the cross-country differences in the level of competition were not explained by overall market size, plausibly because the cost structures and profit margins also differed. Based on their work, Correia, Armada and Veiga (2020) examined the correlation of competitors' entry decision with market size in the Portuguese pharmaceutical market using a probit model. They found that an increase of one million euros in the market revenue (yearly) increases the probability of entry of generics by 0.12 p.p., confirms the existence of endogeneity in the model.

### B. China's Generic Competition Estimation: the Quasi-Hedonic Approach

Using the same quasi-hedonic framework, further research was conducted with a more specific focus on China's market.

Wang (2006) accommodated the quality misalignment of locally manufactured generic goods compared to the global originator by running a global and local product price regression separately. He found that most of the estimations of local generic competition in China were similar to those in the US (Danzon and Chao, 2000). The regression coefficient on generic competition was approximately equal to -0.567, reflecting a highly competitive market in China. However, despite strong evidence of local generic price reduction due to increasing local generic competitors, no responses to additional local generic competition were observed at the global product price level. The empirical results were consistent with the aforementioned suggestion that locally manufactured generics failed to substitute for originators, highlighting the lack of stringent supervision of generic drug quality in China which undermined competition efficiency.

Similar research was conducted by Wu, Xu, Liu and Wu (2014) examined the existence of drug price competition in hospitals under government intervention and the feature of the competition. They also found evidence that generic competition lowered drug price at a statistically significant level, even under the high level of regulation imposed by the Chinese government. This is contradictory to the conclusion drawn by Danzon and Chao (2000) which stated that regulation drives out compe-

tion effects. Additionally, Wu found that the number of therapeutic classes is positively correlated to pharmaceutical prices. The coefficient of the number of generic molecule derivatives (0.187) and the number of generic molecules in the ATC level 5 therapeutic class (0.209) were all positive and statistically significant ( $P < 0.001$ ). This was consistent with neither Wang (2006) nor the theoretical framework and highlighted the distortion of the market pricing system. One plausible explanation given by the authors was that the upward-endogeneity bias might have outweighed tenuous therapeutic effects, resulted in a positive coefficient.

Zhao and Wu (2017) found the same conclusion in more recent research in which they used Tianjin as a case study under quasi-hedonic price modelling. Regarding the competition, they also found that the number of generic competitors had a significantly reduced impact on prices (-0.274,  $P < 0.001$ ), which was consistent with Wu, Xu, Liu and Wu (2014)'s result. The effect of generic drug competition on price was statistically significant (-0.252,  $P < 0.001$ ) for the generic sub-group but insignificant for the originator sub-group. The result also coincided with Wang (2006)'s conclusion.

This mass of literature has provided a brief landscape of competition features in China's pharmaceutical industry. Evidence showed that the generic drug competition successfully reduces price, but the effects acted differently on local and global product subgroups due to the lack of stringent generic quality management. This explanation seems more plausible if the results are compared to Liu, Yang and Hsieh (2012) research on Taiwan's market. The authors used 2SLS regression to investigate the determinants of the regulated price and its impact on the demand for prescription drugs. Their first stage regression was similar to a quasi-hedonic pricing model discussed above. The authors found that the generic competition effect was significant on the price of both local and global products sold in Taiwan's market. This highlighted the difference in generic drug quality between Taiwan and Mainland China back in 2012. Hence it is reasonable to hypothesize that if China manages to improve the quality of generic alternatives, the generic competition effect on price would converge to Taiwan's level. It is also sensible to assume that as a result, higher generic competition would affect both local and global drug prices with statistical significance.

## III. DATA AND METHODOLOGY

### A. Data Source

The main data source for this empirical study is DRUGDATAEXPY (or Yaozh database), which is a health industry data service provider based in China. The historical bidding price records include drug name, company name, dosage form, package information, historical bidding prices, location of the buy-side medical

institution, date of acceptance, and publication source. Another pharmaceutical market data provider, Wuxu Database, was used to obtain supplementary information about the progress of Drug Consistency Evaluation. The dataset contains the status of individual drugs in the evaluation, the latest update of the process, the details of its originator and the market status of the originator (imported or pure foreign market participants). Lastly, Anatomical Therapeutic Chemical (ATC) Classification Code and Defined Daily Dosage (DDD) published by the World Health Organization Collaborating Centre for Drug Statistic Methodology are used. In this paper, the pharmaceutical products are distinguished based on the level 5 ATC code (the same products are identical at the molecular level).

There are 34952 historical bids across 32 types of drugs extracted from the aforementioned database after cleansing. This final dataset covers bidding records from 2008 to February 2021 across 31 provinces in mainland China. The selected sample fulfils several conditions: Firstly, all those sample products have been participating in the domestic pharmaceutical market in China before the enforcement of the Drug Consistency Evaluation. Secondly, the original branded drug or the reference-listed branded drug of these 32 products were either imported to the domestic market or produced by the authorized domestic manufacturer. Either way, this means that the branded drug is competing in the same market as the generics. Thirdly, for each product, bidding information of both branded and generic products should be recorded. The sample contains 4475 bidding records of branded drugs and 30477 records for generic drugs in total. Lastly, within each product category, there exist only one branded drug and multiple generic competitors. This restriction provides a more straightforward interpretation of the generic competition effect on prices when the focus of the analysis is on the branded-drugs subgroup: any increase in competition for each branded product comes from the generics exclusively.

## B. The Quasi-Hedonic Pricing Model

The widely used pricing framework constructed by Rosen (1974), namely the hedonic pricing model, decomposes the price of a product into both internal and external factors that jointly determine the price. However, the effect of market competition on prices, which is the focus of this empirical research, is not articulated by a standard hedonic model. Additionally, the standard model hypothesized a perfectly competitive commercial market. The complexity of the pharmaceutical market violates this assumption: The drug market performance conditions on noisy factors, including intellectual property protection, healthcare schemes, information asymmetry, trust in prescription agencies, alongside other determinants. Thus, a quasi-hedonic approach should be adopted instead.

Danzon and Chao (2000) designed the foremost quasi-hedonic pricing model for pharmaceutical products. The authors argued that the equilibrium prices of drugs were predicted to be inversely related to the number of generic competitors so that

$$\frac{\partial P_{ijk}}{\partial N_j} < 0, \quad (1)$$

where  $P_{ijk}$  refers to the per-unit price of product  $i$  in molecule  $j$  of therapeutic category  $k$  and  $N_j$  refers to the number of generic competitors in molecule  $j$ . The relation is hypothesized to hold under the assumption that the firm follows either Cournot or Bertrand strategy in price setting.

Based on Danzon and Chao (2000)'s model, the implicit price of drug  $i$  from company  $j$  in period  $t$  can be formulated as a function consists of three components in this empirical research:

$$P_{ijt} = f[C_{ijt}, E_{ijt}, Z_{ijt}], \quad (2)$$

where  $C_{ijt}$  refers to market competition,  $E_{ijt}$  is quality attributes, and  $Z_{ijt}$  is other attributes that affect price setting. The dependent variable, drug price ( $P_{ijt}$ ), is a unit price weighted by standard unit and conversion ratios based on the data.

## C. Variable Identification

Based on the aforementioned quasi-hedonic pricing model, historical bidding prices of drugs are used as the dependent variable. The bidding prices, however, strictly depend upon the package and standard dosage of an individual product. Therefore, a standard unit price for individual product is generated based on the bidding prices weighted by package size, unit concentration, and its official defined daily dosage (DDD):

$$P_{ij} = \frac{P_{bid}}{packagesize} \times \frac{DDD}{unitconcentration}. \quad (3)$$

The market competition  $C_{ijt}$  is identified by the number of bids submitted by other companies producing the same product in the same quarter of the year. Under the assumption of no intertemporal correlation of the bidding prices, the price and the competition level in a period are independent of other periods. In this dataset, the level of competition varies within a range from 0 to 348 and has a mean of 44.026.

The quality attributes  $E_{ijt}$  can be decomposed into the characteristics of individual drugs. As a result of the lack of information on manufacturers, one could only identify whether the product is generic or branded. This characteristic is denoted by a dummy variable.

Other attributes  $Z_{ijt}$  include year-specific effects and product-specific effects captured by a vector of years dummy and a vector of product dummy. The province of the buy-side medical institution might also affect the price due to the heterogeneous market regulation enforcement and demand of drugs across the country. For example, drugs with more sophisticated molecules are more demanded in municipalities like Beijing and Shanghai: those cities are associated with provision of more advanced medical treatment. Patients are more likely to go to those cities for treatment if they can.

The distribution of price and competition level are normalised using log transformations. Within each product category, a mean log price of the branded drugs and the generic drugs is also computed accordingly for reference purposes. On average, the mean log prices are 2.651 and 1.242 for branded and generic products respectively. This is consistent with the theoretical assumption that generic drugs are cheaper substitutes for the branded drugs. More detailed descriptive statistics are presented in Appendix C.

## D. The Empirical Methods

### 1. The Within Estimator

To isolate the effects of competition on pharmaceutical prices, a within estimator is employed to eliminate the product and time-period specific effects. The dataset obtained is not typical panel data since the bidding records are not observed at a constant frequency, so year-specific effects are used to proxy the time fixed effect. The product-specific effect are identified based on the level 5 ATC code, and the effect is assumed to be homogenous for products within a product category. Therefore, the fundamental within estimator based on the quasi-hedonic pricing model can be derived as a least square dummy variable regression (LSDV):

$$\log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + u_{ijt}, \quad (4)$$

where  $\log Price_{ijt}$  is the log-transformed standard unit bidding price of product  $i$  from company  $j$  in period  $t$ ,  $\log C_{ijt}$  refers to the measure of competition for an individual product as defined in Section III C,  $Year$  and  $Product$  refers to the vectors of year and product fixed effect dummy variables respectively, and  $u_{ijt}$  is the residual term. It is worthy noting that the coefficients of this quasi-hedonic pricing regression estimate implicit prices of the pharmaceutical attributes, but those coefficients should be interpreted as neither marginal values to consumers nor marginal costs to producers. The coefficient of interest is  $\beta_1$  which estimates the increase in the percentage of price from a percentage increase in competition level.

In addition to the LSDV above, extra variates are included: dummy variable  $BrandedDummy_{ij}$  indicating whether the product is a branded drug and the vector of dummy variable  $Province_{ijt}$  indicating the location of the institution by which the bid is accepted are added. These additional controlled variables will provide supplementary scopes in understanding the effect of generic competition on prices.

Furthermore, the LSDV regression can be applied to the generic and branded drugs sub-groups to identify how drugs with different patent status respond differently to a change in competition. The analysis of the results focuses on branded drug subgroup. This is because of two reasons: First, the branded drugs manufacturers are more stable market players. In comparison, the generic drugs productions are harder to be predicted because the competition effects are more likely to be diversified into factors other than prices, including participation decision, business strategies or other attributes. Meanwhile, any change in competition for branded drugs must necessarily come from the generics. Therefore, the coefficients estimated using the sample of branded-drug subgroup have a more straightforward interpretation and are highly aligned with the interest of this research. Second, the previous literature disagrees on whether there is evidence of generic competition effects on the price of branded drugs in China. This highlights the issues of generic drug qualities which undermined the effectiveness of competition. Therefore, the estimation based on branded-drug subgroup will buttress a more representative and informative evaluation in understanding the impacts of generic drug competition.

### 2. The DiD Estimator

The previous researches argued that the effect of generic competition on branded drug prices in mainland China's pharmaceutical market is less conclusive because the generic products are associated with low quality and poor substitutability (Wang, 2006; Wu, Xu, Liu and Wu, 2014; Zhao and Wu, 2017). In comparison, the studies on Taiwan's market (Liu, Yang and Hsieh, 2012) found evidence of a significant effect of competition on prices among both branded and local generic drugs. In this study, it is hypothesized that more rigorous quality control would amplify the generic competition effect on branded drug prices and lead to a further and more conspicuous reduction in prices of branded drugs in mainland China.

In recent years, the implementation of Drug Consistency Evaluation strengthened the quality management of generic drugs. Accordingly, the generic products, which passed the evaluation after 2016, will be considered as a better substitution of branded drugs. An increase in confidence in domestic generic products is expected, and enlargement in generic competition effect on branded drugs is predicted. Therefore, a difference in difference

(DiD) estimator is constructed to estimate the impact of the reform on prices.

Here, the study focuses on the branded drug subgroup only. The treatment and control group for the DiD estimation are identified based on whether the generic products of individual branded drugs within each product category is certified in the bioequivalence assessment before the date of data extraction (February 2021). In this way, among the 32 pharmaceutical products in the dataset, the treatment group contains 3011 observations across 20 pharmaceutical products whereas the control group contains 1464 observations across 12 pharmaceutical products. The list of drugs of the treatment and control groups are shown in Appendix B.

The DiD specification, in this case, can be simply derived as:

$$\log Price_{ijt} = \gamma_0 + \gamma_1 Product + \gamma_2 Year + \gamma_3 Treatment_i * Post_t + v_{ijt}, \quad (5)$$

where, again, the  $\log Price_{ijt}$  refers to the log-transformed price of the drug  $i$  from the company  $j$  observed in period  $t$ , the  $Product$  is the vector of product dummy indicates product-specific fixed effects and the  $Year$  is the vector of year dummy proxies time-specific fixed effects in the estimation. The interaction variable  $Treatment_i * Post_t$  is a multiplication of the treatment indicator and the post-reform period indicator. The interaction variable switches on in 2016 if the product is in the treatment group and then stays on thereafter. The coefficient of interest is  $\gamma_3$ , captures the effect of the treatment on prices of branded drugs. The  $\gamma_3$  is expected to be negative, which implies that the reform enhanced substitutability of the certified generic products thus strengthened the effect of generic competition on prices of branded drugs.

This empirical approach relies heavily on the assumption of parallel trends of outcomes in treatment and control groups in absence of intervention. In other words, since year dummies and product fixed effects are controlled in the regression, the only factor that induced changes in output over time in the treatment group compared to the control group is the 2016 Drug Consistency Evaluation. In this way, the  $\gamma_3$  demonstrate causal effect.

To examine whether the common trend assumption holds, a graph of the change in average  $\log Price$  for the treatment and control group over time is plotted. Showing in Figure 1 below, the general trend of change in  $\log Price$  does not seem to be parallel in the two experimental groups before 2016. This might be due to the divergence in the average price of the different products and the difference in the composition of products participating in bidding each year. The interest of the study is on whether the common trend assumption holds in absence of product-specific effects to ensure that the only change in output is induced by the policy. Therefore, a new variable is constructed by computing the difference between the  $\log Price$  and the mean of  $\log Price$  of

individual branded drug:

$$Dif \log Price_{ijt} = \log Price_{ijt} - \log \bar{Price}_{ijt}. \quad (6)$$

Showing the in Figure 2 below, one may confirms that the common trend assumption holds the output variable  $\log Price$  for an individual product is demeaned, which eliminates product fixed effects to some extent. Accordingly, one could adapt the DiD estimator as

$$Dif \log Price_{ijt} = \delta_0 + \delta_1 Product + \delta_2 Year + \delta_3 Treatment_i * Post_t + s_{ijt}. \quad (7)$$

In fact, the new coefficient of interest, which is  $\delta_3$  in this case, is equivalent to  $\gamma_3$ . This is because that the demeaning process is a simple linear transformation. It is absorbed in the product-specific effects, changes the coefficient  $\gamma_1$  to  $\delta_1$ . Therefore, the output variable  $Dif \log Price_{ijt}$  and  $\log Price_{ijt}$  are interchangeable if the only parameter of interest is the coefficient of the interaction variable. This validate the common trend assumption, therefore  $\delta_3$  estimates the impact of the Drug Consistency Evaluation on the price of branded drugs. Competition can also be added as a controlled variate to obtain additional information.

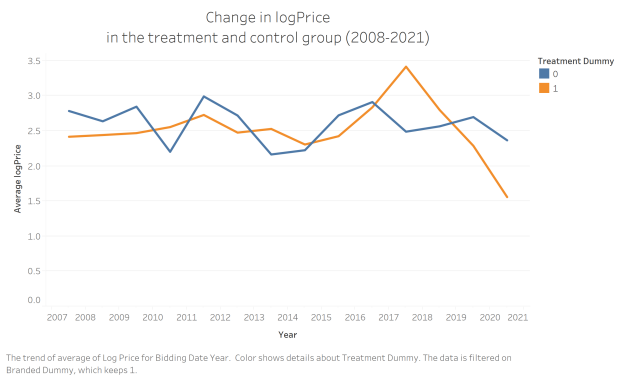


FIG. 1.  $\log Price$ : no common trend observed

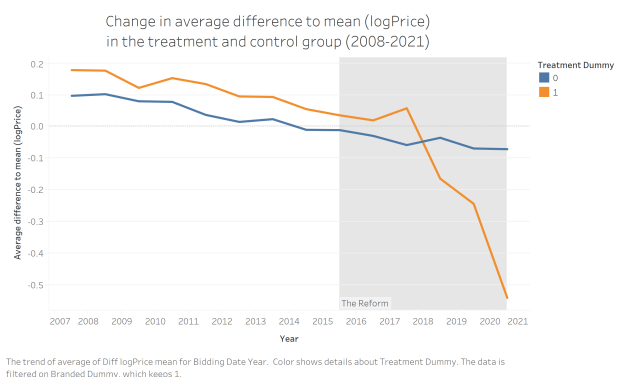


FIG. 2.  $Dif \log Price$ : Common trend observed

## IV. RESULTS AND EXPLANATION

### A. The Correlation Between Generic Competition and the Pharmaceutical Prices

Figure 3 below shows an extracted result<sup>2</sup> of the within estimator based on the quasi-hedonic pricing model proposed in the previous section. Column (1) to (3) shows the regression estimation using the full sample where (2) added Branded Dummy as a variate and (3) controlled for both branded dummy and province-specific effects. In general, a negative correlation between competition and price at a statistically significant level is found. The elementary fixed-effect estimator predicted that a percentage increase in competition will reduce the bidding price of a pharmaceutical product by about 0.061 per cent ( $p < 0.01$ ) on average. The coefficient become -0.053 ( $p < 0.01$ ) if the extra controlled variables are added, but the effect is still considered to be negative and statistically significant. It is also interesting to know that the coefficient on the branded dummy in regression (3) is 0.973 ( $p < 0.01$ ), indicates that under the *ceteris paribus* condition, the branded products will be about 97.3% higher in the price of its generics.

VARIABLES	the Within Estimator						
	(1) logPrice	(2) logPrice	(3) logPrice	(4) logPrice	(5) logPrice	(6) logPrice	(7) logPrice
logCompetition	-0.061*** (0.005)	-0.045*** (0.005)	-0.053*** (0.005)	-0.021*** (0.005)	-0.025*** (0.005)	-0.051*** (0.005)	-0.061*** (0.005)
BrandedDummy		0.953*** (0.012)	0.973*** (0.011)				
Constant	2.052*** (0.033)	1.852*** (0.031)	1.988*** (0.034)	2.843*** (0.026)	2.890*** (0.032)	1.864*** (0.034)	2.016*** (0.037)
Observations	34,592	34,592	34,592	4,293	4,293	30,299	30,299
R-squared	0.053	0.207	0.242	0.200	0.224	0.056	0.108
Number of ATC1	32	32	32	32	32	32	32
Adjusted R-squared	0.0521	0.206	0.241	0.192	0.210	0.0544	0.106

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

FIG. 3. Result Table: the Within Estimator

Column (4) and (5) shows the result of the within estimator with and without controlling province-specific effect respectively using the branded-drug subgroup samples. Similarly, regression (6) and (7) used generic subgroups. In all cases, evidence of negative generic competition effect on pharmaceutical prices at a 1% significant level are found, but the magnitudes of the effect differ. The result suggests that the prices of generic products are much more responsive to a change in the competition: a percentage change in competition results in a 0.025% reduction in the price of a branded product or a 0.061% reduction in the price of a generic product. One explanation is that the local generic manufactures are smaller firms compared to the authorized branded drug manufacturers. The multi-national company producing

the branded drugs holds dominant positions in the high-end market. Those global market participants are more advance in research and production competence. The local generic manufactures in China, on the other hand, are small enterprises and are weaker in technology level, manufacturing practices, and management system (Chan and Daim, 2011). In fact, the top 10 local pharmaceutical enterprises in China accounts for 10% of the total sales revenue and the top 100 firms account for 33%, whereas the top ten international pharmaceutical companies account for about 42% of global pharmaceutical sales revenue (Sun, Santoro, Meng, Liu and Eggleston, 2008). The market concentration and composition made the local generic producers more sensitive to competition in price. Another explanation is, again, the lack of generic drug quality control. This demolished the substitutability and thus the local generic competition exerts less pressure on branded drugs. The branded drugs with a higher reputation are believed to have more stable demand compared to generic products.

### B. The Impact of the Reform

The study will focus on investigating the effect of generic competition on branded drug prices in the following sections as discussed in Section III D 1. Although evidence shows a negative correlation between generic competition and the price of branded products at a statistically significant level, it is also important to note that the effect estimated are heterogeneous over time. Previous researchers did not find such a significantly negative correlation (Wang, 2006; Wu, Xu, Liu and Wu, 2014; Zhao and Wu, 2017), and the effect is revealed only if more recent data are employed. Taking the implementation of the pharmaceutical market reform in China in recent years into consideration, the coefficient of interest estimated is -0.030 ( $p < 0.01$ ) if only bidding records after 2016 were used. In comparison, there is no evidence that generic competition reduces branded drug price before 2016 as shown in Figure 4.

Previous researchers suggested that low quality is the key factor that undermined the effect of generic competition on branded drugs in China. Under more stringent quality control of the generic product, the competition effect should start to emerge, and the prices of branded drugs would decline. A DiD estimator is used to examine the impact of such quality control in the context of the implementation of Drug Consistency Evaluation. The results are shown in Figure 5 below: Column (10) presents the result of the estimation using the fundamental DiD estimator, and column (11) included the measure of competition as an additional controlled variable. The common trend assumption is fulfilled as discussed in Section III D 2.

The result shows that the reform has a statistically significant negative impact on the price of the branded drug. By controlling the level of competition, the prices

<sup>2</sup> The detail of each regression specification can be found in Appendix A.

the Within Estimator (Branded Sub-Group)		
VARIABLES	(8) logPrice	(9) logPrice
logCompetition	-0.000 (0.007)	-0.030*** (0.007)
Constant	2.556*** (0.035)	2.912*** (0.036)
Observations	1,629	2,664
R-squared	0.099	0.183
Number of ATC1	32	32
Adjusted R-squared	0.0590	0.162

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

FIG. 4. Result Table: the Within Estimator (Branded)

the DiD Estimator		
VARIABLES	(10) Diff logPrice	(11) Diff logPrice
logCompetition		-0.020*** (0.005)
Treatment*Post_Reform	-0.072*** (0.015)	-0.078*** (0.016)
Constant	0.087** (0.034)	0.135*** (0.037)
Observations	4,475	4,293
R-squared	0.201	0.206
Adjusted R-squared	0.192	0.197

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

FIG. 5. Result Table: the DiD Estimator

of the branded drug will be reduced by 7.8% after the treatment. It means, if a branded drug had generic substitutes within the same product category certified in the evaluation, it experiences higher pressure from generic competition. This is because that the quality of those certified generic drugs is secured. Improvement in substitutability forces the branded drugs to participate in price competition to maintain their market share. Since the branded drugs usually charge much higher prices relative to generic products, the price of the branded drugs will be largely depressed to restore their market competitiveness after the reform.

## V. DISCUSSION AND LIMITATION

### A. Summary of Findings

Firstly, by estimating the quasi-hedonic pricing model using a within estimator, one could identify the negative generic competition effects on pharmaceutical prices at a statistically significant level in Mainland China using data of both subgroups from 2008 to 2021. One may also

noticed that the impact of generic competition is heterogeneous over time. Although conspicuous negative effects in branded drug subgroup at a 1% significant level are observed using more recent data since 2016, there is no evidence of such a negative correlation before 2016. Additionally, under *ceteris paribus* conditions, the branded drug prices exceeded the price of its generics by a tremendous amount.

Secondly, the results of the DiD estimator allowed us to conclude that the Drug Consistency Evaluation, which strengthens the quality control of the generic products, indeed reduced the prices of branded drugs to a large extent. For patented drugs having their generic substitutions certified in the evaluation after 2016, the reform enhanced the generic competition effect, enlarged the downward pressure on the prices of the branded drugs. The result corroborates the argument that the lack of quality control in previous years demolished the generic competition effect on branded product. The hypothesis is proved to hold that the effect becomes negative at a statistically significant level under more stringent quality control.

### B. Beyond the Empirical Results

There are several findings beyond the aforementioned empirical results that are worth mentioning.

Firstly, a negative correlation between competitions and prices is found. This corroborates with previous literature, but the magnitude differs. In this study, the coefficients of interest estimated from the fixed-effect estimator are much smaller compared to the literature. For example, [Zhao and Wu \(2017\)](#) estimated the effect to be -0.274 (p<0.01) using the full sample in comparison to the -0.061 (p<0.01) in this estimation. Note that those coefficients are not directly comparable since the interpretations are different. One aspect is that the measurements of competition are different. In this paper, the level of competition is measured based on the number of bids whereas [Zhao and Wu \(2017\)](#) used the number of manufacturers within the same molecule. The predicted 0.274% reduction in pharmaceutical prices they estimated is associated with a percentage change in the number of manufacturers. A 1% increase in the number of manufacturers will usually result in a higher percentage change in this measure of competition because firms commonly submit multiple bids in one period. Therefore, the divergence in magnitude of the coefficient does not necessarily imply a conflict between this empirical result and previous literature. Other measurements of competition are also considered, including the number of generic manufacturers. However, the bidding records are regarded as a better depiction of the market-oriented competition. On one hand, it offers sizable variation in this independent variable compared to using the number of manufacturers. On the other hand, it explains the disparity in prices bids by different companies in the same period while facing the same number of competi-



tors. Competitors differ in the activeness of market participation lead to a heterogeneous level of competitive pressure. Thus, the individual bid from the contenders should be considered as an independent source of competition. Future research may try to develop new measurements of competition.

Secondly, in Figure 2, a parallel trend in branded drug prices over time before 2016 is observed, alongside with a divergence after the reform. However, it is interesting that the divergence did not happen immediately after the enforcement of the Drug Consistency Evaluation in 2016. Instead, it is also observed that the beginning of the change in trend in the treatment group occurred between 2017-2018. One explanation is that the Drug Consistency Evaluation is a slow and ongoing process that takes time. It is not the case that all the generic products for the drugs in the treatment group passed the evaluation simultaneously: the time the drugs start the evaluation is different and the length of the process may depend on the complexity of the molecules. In fact, most of the generic products of the drugs in the treatment group were not certified in the evaluation until 2018 or late 2017. Due to the data limitation of this research, it is almost impossible to track the exact date that individual firms passed the assessment. This might lead to an underestimation of the actual impact of the reform, but it does not affect the conclusion that there is indeed evidence of the negative correlation between generic competition and branded drug price under more strict quality control in Mainland China. One could still obtain policy-relevant inference from the estimation, but if future researchers are interested in estimating the true magnitude of the impact, a more detailed dataset should be used.

### C. Limitations and Suggestions for Future Studies

One of the fundamental limitations is the data limitation. Most of the data service providers of this industry are commercial, which made data extraction challenging. The lack of data accessibility constrained the sample size and the details of relevant product attributes. Other than the data, there are several limitations of this empirical estimation that need to be addressed.

Firstly, the endogeneity issues within the quasi-hedonic pricing model remained to be concerning. There likely exists a positive and reversed causal effect of pharmaceutical price on the level of competition that may lead to an underestimation of the actual generic competition effect. The origin of the endogeneity can be decomposed into firms' market entry decision and institutions' bids acceptance decision. The former source of endogeneity has been discussed thoroughly by previous researchers that despite the high entry costs and barriers, the production of generic drugs is inexpensive once the manufacturer grasped the essential synthesis pathways of the compound and once economies of scales are achieved.

The higher pharmaceutical price, which is usually associated with higher profit for the producers, encourages profit-seeking firms to participate in the market and generates a higher level of competition. The endogeneity issue due to the institutions' bids acceptance decision, on the other hand, can be regarded as a demand-driven factor that pushed competition to concentrate on drugs with higher prices. The medical institutions have a preference towards the drugs with a higher price to some extent because the medical providers are allowed with a 15% markup on drug sales in China. The markup will generate higher nominal income from more expensive products to subsidize medical services (Wu, Xu, Liu and Wu, 2014). In short, these two aspects of the endogeneity embedded within the model complicates the estimation. The estimation result might be biased potentially, and the generic competition effects are likely to be underestimated.

Secondly, the fundamental assumptions of the within estimator might be violated. By employing the fixed effect estimator, an implicit assumption has been made, assuming that the product-specific effects are time-invariant. However, the product fixed effects on price might respond to other factors, including market composition, development of production technology, or even changes in a foreign market or R&D progress. Due to the complexity of the pharmaceutical market, it is infeasible to control all the variates. Even with a more complete dataset, there may still exist unobservable characteristics. Or one may encounter an over-identification issue that leads to a less conclusive result. Similarly, the period fixed effect is proxied by the year specific effect under the assumption that this effect is constant throughout the year and is different across years. There is no perfect measurement of period fixed effect for this dataset since it is not a typical panel data observed at a regular frequency. Future researchers could try to use an alternative dataset or appropriate instrumental variables to eliminate this concern if feasible.

Thirdly, it is reasonable to question whether there exists an intertemporal correlation between prices and factors in other periods. Firms may need time to observe and respond to a change in the market. In particular, firms' expectation of the current period might be based on the prices and other attributes in the previous periods. Thus, for instance, the current bidding price might be affected by competition and prices in the previous period, and the current competition level might be determined by the previous periods' market performance. These possibilities also complicate the model, and the direction of bias remained ambiguous.

Fourthly and most importantly, the therapeutic competition effect<sup>3</sup> is omitted. This is largely due to limited data accessibility: there is insufficient information to

<sup>3</sup> This refers to a broader concept of competition from the competitors producing drugs that contain different molecules within the

identify the therapeutic competitions. These therapeutic competitors can also be associated as indirect “substitutes” other than a generic drug. Omitting the therapeutic competition effect from the model leads to biased estimation of the generic competition effect, but the extent of the bias depends on the closeness of the therapeutic competitors within each product category. [Danzon and Chao \(2000\)](#) have argued that therapeutic competition is negatively correlated to pharmaceutical prices in theory, but researchers who investigated China’s market reached a consensus in neither the direction nor the magnitude of this effect on drug prices. Thus, it is worthy to conduct further investigation on this ambiguous effect in the future. The existence of therapeutic effect also raises concerns of identifying treatment and control group in the DiD specification. If the impact of the treatment spilt over to the control group, the interpretation of the estimated results might be misleading. In fact, based on the ATC codes, some of the products in the control group can be classified as therapeutic derivatives of a drug in the treatment group. The validity of the causal effect estimated is under threats.

Lastly, whether the current quasi-hedonic pricing model is the best predictor remains questionable. The complexity of the pharmaceutical market gives rise to too many noisy factors that jointly determine prices. The inclusion of extra variates in the model is also considered, for example, the company’s activeness of participation in each period. However, these market factors may potentially perplex the interpretation of the result. The current model is sufficient to provide essential policy-relevant inferences in the context of this dissertation, but a more detailed model offers a more accurate estimation of the actual magnitude of individual factors’ impact on prices and will help us to gain a more profound understanding of the price determination process in the pharmaceutical market. In addition to the inclusion of extra variates, one may also extend the model beyond a linear specification. Future studies may select a model that involves non-linear characteristics, for example, the diminishing marginal effect of competition on prices.

#### D. Policy Implications

According to the results, more stringent quality control of the generic product enhanced the competition effects and reduced pharmaceutical prices effectively. There are a few policy implications that can be drawn from this research, and those inferences might apply to other LMICs if they have similar market structures as China.

Firstly, the Drug Consistency Evaluation has achieved remarkable success so far, and the continuous enforcement and generalisation of the evaluation are crucial.

The evaluation requires time and efforts, but the potential welfare gain is tremendous. Consumers benefit from not only the improvement in general drug quality but also the affordability of pharmaceutical products in the market. Those are extremely pivotal signs of progress in the improvement of social welfare and living standards of households in developing countries like China. A more affordable medical service system ameliorates the health conditions of citizens, loosens households’ budget constraint, and yield further economic benefits.

Secondly, authorities should be aware of the corruptions which these policies can engender ([Sun, Santoro, Meng, Liu and Eggleston, 2008](#); [Yang, Chen and Wang, 2009](#)). The magnification of generic competition effect on branded drug prices is largely based on the increase in confidence in certified generic products. Hence, the evaluation should follow the official protocol strictly to maintain the credibility of the assessment outcome. Additionally, the regulation on drug registration should also be strengthened. China offers more generous price policies on new drugs to incentivize research and innovation. The Drug Consistency Evaluation has increased the cost associated with generic drugs production and registration, and thus some manufacturers may tend to corrupt with the registration authorities to qualify their product into a “new-drug” category by applying minor changes in the compound ([Wu, Xu, Liu and Wu, 2014](#)). Thus, it is of the essence for policymakers to carefully assess these potential consequences.

Thirdly, the market-focused regulation should be intensified to create effective market environments. For instance, collusion prevention policies should be taken into consideration. Any distortion of the market competition efficiency will mitigate the effect of the generic competition and the impact of the reform on branded pharmaceutical prices.

Lastly, the information on generic drugs should be more accessible to the public. The medical institutions are the direct players in the bidding mechanism of drugs, but the fundamental source of demand is still the general public. Although the quality of the certified generic products is secured under rigorous regulations and assessments, there is still a large proportion of the population who believe that the generic products are ineffective or have excessive side effects. Therefore, it is necessary for the authorities to clarify the nature of generic products, and to establish or restore trust in the local generic drugs.

## VI. CONCLUSION

Using a quasi-hedonic pricing model estimated by a within estimator, the paper presents evidence of a negative generic competition effect on pharmaceutical prices at a statistically significant level in Mainland China in both generic and branded drug subgroups. The generic competition effect on branded drug prices only started to emerge recently. The results coincided with the ma-

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same therapeutic class. The therapeutic competition is defined in Section II A

majority of the arguments raised in previous literature. According to the DiD model estimated, the Drug Consistency Evaluation in 2016 successfully reduced the prices of branded drugs. The finding corroborates the argument that the lack of quality control is the key factor that demolished generic competition effect on branded product. Therefore, strengthening the generic products' quality supervision will enhance the generic competition effect on pharmaceutical prices, and will lead to an im-

provement in households' social welfare. This paper can be an insightful reference highlights the pivotal role of a stringent regulation on generic drug qualities for markets like Mainland China to mitigate the market distortions and to reap the full benefits of competition. Meanwhile, the pharmaceutical market is extremely complex. Future research should tackle the investigation from multiple dimensions to compute a better prediction of the market.

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- CAMERON, A, HILL, S AND WHYTE, P (2015): "WHO Guideline on country pharmaceutical pricing policies. Geneva: World Health Organization", *World Health Organization, Geneva*.
- CAMERON, ALEXANDRA, MANTEL-TEEUWISSE, AUKJE K., LEUFKENS, HUBERT GM AND LAING, RICHARD OGILVIE (2012): "Switching from originator brand medicines to generic equivalents in selected developing countries: how much could be saved?", *Value in health*, 15(5), 664–673.
- CAVES, RICHARD E., WHINSTON, MICHAEL D., HURWITZ, MARK A., PAKES, ARIEL, TEMIN, PETERL AND M.WEBER(1991): "Patent expiration, entry, and competition in the US pharmaceutical industry", *Brookings papers on economic activity. Microeconomics*, 1991, 1–66.
- CHAN, LEONG AND DAIM, TUGRUL U. (2011): "Multi-perspective analysis of the Chinese pharmaceutical sector: Policy, enterprise and technology", *Journal of Technology Management in China*, 2011.
- CORREIA, ISABEL, ARMADA, LUÍS AND VEIGA, PAULA(2020): "Generics competition in the Portuguese pharmaceutical market", *Journal of Generic Medicines*, 1741134320953875.
- DANZON, PATRICIA M. AND CHAO, LI-WEI(2000): "Does regulation drive out competition in pharmaceutical markets?", *The Journal of Law and Economics*, 43(2), 311–358.
- DANZON, PATRICIA M. AND FURUKAWA, MICHAEL F.(2011): "Cross-national evidence on generic pharmaceuticals: pharmacy vs. physician-driven markets", *National Bureau of Economic Research*.
- DANZON, PATRICIA M., MULCAHY, ANDREW W. AND TOWSE, ADRIAN K.(2015): "Pharmaceutical pricing in emerging markets: effects of income, competition, and procurement", *Health economics*, 24(2), 238–252.
- DI MASI, JOSEPH A. AND PAQUETTE, CHERIE(2004): "The economics of follow-on drug research and development", *Pharmacoeconomics*, 22(2), 1–14.
- GRABOWSKI, HENRY(2004): "Are the economics of pharmaceutical research and development changing?", *Pharmacoeconomics*, 22(2), 15–24.
- HUANG, BAOBIN, BARBER, SARAH L., XU, MINGZHE AND CHENG, SHUANGHONG(2017): "Make up a missed lesson-New policy to ensure the interchangeability of generic drugs in China", *Pharmacology research & perspectives*, 5(3).
- KAPLAN, WARREN A., RITZ, LINDSAY SARAH, VITELLO, MARIE AND WIRTZ, VERONIKA J.(2012): "Policies to promote use of generic medicines in low and middle income countries: a review of published literature, 2000–2010", *Health policy*, 106(3), 211–224.
- KREMER, MICHAEL(2002): "Pharmaceuticals and the developing world", *Journal of Economic Perspectives*, 16(4), 67–90.
- LICHTENBERG, FRANK R.(2014): "Pharmaceutical innovation and longevity growth in 30 developing and high-income countries, 2000–2009", *Health Policy and Technology*, 3(1), 36–58.
- LIU, YA-MING, YANG, YEA-HUEI KAO AND HSIEH, CHEE-RUEY(2012): "Regulation and competition in the Taiwanese pharmaceutical market under national health insurance", *Journal of health economics*, 31(3), 471–483.
- MIKULIC, MATEJ(Nov. 2020): "Topic: Global pharmaceutical industry", Available at: <https://www.statista.com/topics/1764/global-pharmaceutical-industry/>
- RIDA, NADA ABDEL AND IBRAHIM, MOHAMED IZHAM MOHAMED(2018): "Medicines pricing policy and strategies in developing countries: A review", *Social and administrative aspects of pharmacy in low-and middle-income countries*, 111–128.
- SUN, JING, REN, LUO AND WIRTZ, VERONIKA(2016): "How much could be saved in Chinese hospitals in procurement of anti-hypertensives and anti-diabetics?", *Journal of medical economics*, 19(9), 881–888.
- SUN, QIANG, SANTORO, MICHAEL A., MENG, QINGYUE, LIU, CAITLIN AND EGGLESTON, KAREN(2008): "Pharmaceutical policy in China", *Health affairs*, 27(4), 1042–1050.
- WANG, Y. RICHARD(2006): "Price competition in the Chinese pharmaceutical market", *International Journal of Health Care Finance and Economics*, 6(2), 119–129.
- WOOD, LAURA(Jan. 2020): "Growth Insights on China's Pharmaceutical Industry, Forecast to 2025", Available at: [https://www.researchandmarkets.com/reports/4968410/growth-insights-on-chinas-pharmaceutical?utm\\_source=dynamic&utm\\_medium=BW&utm\\_code=3tk4mv&utm\\_campaign=1348829-Growth+Insights+on+China's+Pharmaceutical+Industry+\(2020+to+2025\)-Key+Market+Trends+Supporting+the+Expansion+of+the+Chinese+Pharmaceutical+Industry&utm\\_exec=jamu273bwd](https://www.researchandmarkets.com/reports/4968410/growth-insights-on-chinas-pharmaceutical?utm_source=dynamic&utm_medium=BW&utm_code=3tk4mv&utm_campaign=1348829-Growth+Insights+on+China's+Pharmaceutical+Industry+(2020+to+2025)-Key+Market+Trends+Supporting+the+Expansion+of+the+Chinese+Pharmaceutical+Industry&utm_exec=jamu273bwd)
- WU, JING, XU, JUDY, LIU, GORDON AND WU, JI-HONG(2014): "Pharmaceutical pricing: an empirical study of market competition in Chinese hospitals", *Pharmacoeconomics*, 32(3), 293–303.
- YU, XUAN, LI, CHENG, SHI, YUHUA AND YU, MIN(2010): "Pharmaceutical supply chain in China: current issues and implications for health system reform", *Health policy*, 97(1), 8–15.
- ZHANG, Y. PHILIP AND DENG, MICHELLE M(2008): "Enforcing pharmaceutical and biotech patent rights in China", *Nature biotechnology*, 26(11), 1235–1240.
- ZHAO, MINGYUE AND WU, JING(2017): "Impacts of regulated competition on pricing in Chinese pharmaceutical market under urban employee basic medical insurance", *Expert*

review of pharmacoeconomics & outcomes research, 17(3), 311-320.

ZHANG, M. AND BIAN, Y(2007): “History and effect of Chinese hospital pharmaceutical mark-up policy”, *J Chin Med Care Admin.*

ROSEN, SHERWIN(1974): “Hedonic prices and implicit markets: product differentiation in pure competition”, *Journal of political economy*, 82(1), 34–55.

YANG, SJ, CHEN, JING AND WANG, SL(2009): “Promote the development of imita-tion pharmaceuticals in China”, *World Clin Drugs*, 30, 121–4.

## Appendix A: Regression Specifications

### The Within Estimators

Full Sample:

$$(1): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + u_{ijt}$$

$$(2): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + \beta_4 BrandedDummy + u_{ijt}$$

$$(3): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + \beta_4 BrandedDummy + \beta_5 Province + u_{ijt}$$

For Branded Drug Subgroup:

$$(4): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + u_{ijt}$$

$$(5): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + \beta_4 Province + u_{ijt}$$

For Generic Drug Subgroup:

$$(6): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + u_{ijt}$$

$$(7): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + \beta_4 Province + u_{ijt}$$

For Branded Drug Subgroup (Before 2016)

$$(8): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + \beta_4 Province + u_{ijt}$$

For Branded Drug Subgroup (After 2016)

$$(9): \log Price_{ijt} = \beta_0 + \beta_1 \log C_{ijt} + \beta_2 Year + \beta_3 Product + \beta_4 Province + u_{ijt}$$

### The DiD Estimators (Branded Drug Subgroup Only)

$$(10): Dif \log Price_{ijt} = \delta_0 + \delta_1 Product + \delta_2 Year + \delta_3 Treatment_i * Post_t + s_{ijt}$$

$$(11): Dif \log Price_{ijt} = \delta_0 + \delta_1 Product + \delta_2 Year + \delta_3 Treatment_i * Post_t + \delta_4 C_{ijt} + s_{ijt}$$

## Appendix B: List of Drugs in the Treatment and Control Groups

Tabulation of ATC TreatmentDummy

ATC	TreatmentDummy		
	0	1	Total
A01AB18	72	0	72
A01AD05	163	0	163
A02BC02	0	79	79
A02BC03	127	0	127
A07BC05	0	167	167
A10BB12	0	193	193
A10BF03	145	0	145
B01AC03	0	50	50
C03BA11	0	46	46
C08CA01	0	213	213
C09AA02	0	74	74
C09CA04	0	67	67
C10AA01	0	136	136
C10AA05	0	470	470
C10AA07	0	179	179
D01AE15	32	0	32
D07AA01	292	0	292
G04BE03	0	154	154
H01CB02	127	0	127
J01DB09	0	123	123
J01DH51	62	0	62
L01BA04	0	239	239
M01AC05	20	0	20
M05BA02	77	0	77
N03AF01	159	0	159
N03AF02	188	0	188
N03AX14	0	149	149
N05AH03	0	117	117
N06AX21	0	211	211
R03DC03	0	117	117
R05CB06	0	75	75
S01AA27	0	152	152
Total	1464	3011	4475

## Appendix C: Detailed Descriptive Statistics

Summary statistics: N mean sd min max by( ATC)					
ATC	N	mean	sd	min	max
A01AB18	767.000	2.464	0.779	-2.177	3.944
A01AD05	2228.000	-1.963	1.142	-5.481	3.562
A02BC02	782.000	3.122	0.769	1.460	4.696
A02BC03	929.000	1.549	0.352	0.157	2.595
A07BC05	1296.000	1.004	0.597	-2.120	3.421
A10BB12	2083.000	-0.197	1.061	-3.696	1.915
A10BF03	581.000	1.329	0.284	0.008	1.974
B01AC03	1288.000	1.889	0.542	0.863	2.938
C03BA11	1067.000	-1.133	1.014	-3.139	2.357
C08CA01	2514.000	0.044	0.931	-4.605	3.425
C09AA02	1247.000	-0.073	0.535	-2.055	1.827
C09CA04	1323.000	0.433	0.656	-1.507	1.608
C10AA01	1092.000	0.447	0.924	-1.842	2.393
C10AA05	1153.000	1.707	0.911	-1.588	2.830
C10AA07	1775.000	1.393	0.664	-1.609	2.357
D01AE15	857.000	1.380	0.423	0.095	2.975
D07AA01	1399.000	2.679	0.342	0.597	3.515
G04BE03	560.000	3.374	0.903	1.152	4.220
H01CB02	1741.000	3.619	0.957	0.405	6.750
J01DB09	1163.000	1.087	0.836	-0.083	8.294
J01DH51	977.000	5.317	0.302	2.779	6.612
L01BA04	1161.000	6.967	0.535	6.154	8.251
M01AC05	225.000	1.140	0.120	0.928	1.604
M05BA02	264.000	3.698	0.406	3.283	6.446
N03AF01	975.000	0.260	0.967	-1.295	3.325
N03AF02	495.000	2.096	0.402	1.201	3.140
N03AX14	756.000	2.863	0.265	2.339	3.611
N05AH03	889.000	2.482	0.679	-1.617	3.930
N06AX21	330.000	2.754	0.209	2.246	3.103
R03DC03	516.000	2.037	0.921	-1.113	2.923
R05CB06	657.000	3.619	0.637	1.112	5.375
S01AA27	1862.000	0.538	0.554	-0.844	1.692

#### Descriptive Statistics Branded Drug

Variable	Obs	Mean	Std. Dev.	Min	Max
logPrice mean	4475	2.651	1.772	-0.697	7.662

#### Descriptive Statistics Generic Drug

Variable	Obs	Mean	Std. Dev.	Min	Max
logPrice mean	30477	1.242	1.890	-2.063	6.787

#### Descriptive Statistics Competition

Variable	Obs	Mean	Std. Dev.	Min	Max
Competition	34952	44.026	44.936	0.000	348.000

#### Tabulation of BrandedDummy TreatmentDummy

BrandedDummy	TreatmentDummy		
	0	1	Total
0	9974	20503	30477
1	1464	3011	4475
Total	11438	23514	34952

Tabulation of BrandedDummy logPrice\_mean when ATC is A01AB18

BrandedDummy	logPrice_mean		Total
	2.336609	3.696694	
0	695	0	695
1	0	72	72
Total	695	72	767

Tabulation of BrandedDummy logPrice\_mean when ATC is A01AD05

BrandedDummy	logPrice_mean		Total
	-2.06346	-.6966482	
0	2065	0	2065
1	0	163	163
Total	2065	163	2228

Tabulation of BrandedDummy logPrice\_mean when ATC is A02BC02

BrandedDummy	logPrice_mean		Total
	2.950456	4.644351	
0	703	0	703
1	0	79	79
Total	703	79	782

Tabulation of BrandedDummy logPrice\_mean when ATC is A02BC03

BrandedDummy	logPrice_mean		Total
	1.440622	2.235706	
0	802	0	802
1	0	127	127
Total	802	127	929

Tabulation of BrandedDummy logPrice\_mean when ATC is A07BC05

BrandedDummy	logPrice_mean		Total
	.9010819	1.696	
0	1129	0	1129
1	0	167	167
Total	1129	167	1296

Tabulation of BrandedDummy logPrice\_mean when ATC is A10BB12

BrandedDummy	logPrice_mean		Total
	-.3685801	1.486378	
0	1890	0	1890
1	0	193	193
Total	1890	193	2083

Tabulation of BrandedDummy logPrice\_mean when ATC is A10BF03

BrandedDummy	logPrice_mean		Total
	1.24048	1.593505	
0	436	0	436
1	0	145	145
Total	436	145	581

Tabulation of BrandedDummy logPrice\_mean when ATC is B01AC03

BrandedDummy	logPrice_mean		Total
	1.869514	2.371046	
0	1238	0	1238
1	0	50	50
Total	1238	50	1288

Tabulation of BrandedDummy logPrice\_mean when ATC is C03BA11

BrandedDummy	logPrice_mean		Total
	-1.197123	.2925824	
0	1021	0	1021
1	0	46	46
Total	1021	46	1067

Tabulation of BrandedDummy logPrice\_mean when ATC is C08CA01

BrandedDummy	logPrice_mean		Total
	-.0846314	1.432484	
0	2301	0	2301
1	0	213	213
Total	2301	213	2514

Tabulation of BrandedDummy logPrice\_mean when ATC is C09AA02

BrandedDummy	logPrice_mean		Total
	-.1005966	.3661915	
0	1173	0	1173
1	0	74	74
Total	1173	74	1247

Tabulation of BrandedDummy logPrice\_mean when ATC is C09CA04

BrandedDummy	logPrice_mean		Total
	.3815852	1.389575	
0	1256	0	1256
1	0	67	67
Total	1256	67	1323

Tabulation of BrandedDummy logPrice\_mean when ATC is C10AA01

BrandedDummy	logPrice_mean		Total
	.3098771	1.412973	
0	956	0	956
1	0	136	136
Total	956	136	1092

Tabulation of BrandedDummy logPrice\_mean when ATC is C10AA05

BrandedDummy	logPrice_mean		Total
	1.361764	2.209191	
0	683	0	683
1	0	470	470
Total	683	470	1153

Tabulation of BrandedDummy logPrice\_mean when ATC is C10AA07

BrandedDummy	logPrice_mean		Total
	1.326909	1.986668	
0	1596	0	1596
1	0	179	179
Total	1596	179	1775

Tabulation of BrandedDummy logPrice\_mean when ATC is D01AE15

BrandedDummy	logPrice_mean		Total
	1.340227	2.405505	
0	825	0	825
1	0	32	32
Total	825	32	857

Tabulation of BrandedDummy logPrice\_mean when ATC is D07AA01

BrandedDummy	logPrice_mean		Total
	2.658635	2.758338	
0	1107	0	1107
1	0	292	292
Total	1107	292	1399

Tabulation of BrandedDummy logPrice\_mean when ATC is G04BE03

BrandedDummy	logPrice_mean		Total
	3.20078	3.82936	
0	406	0	406
1	0	154	154
Total	406	154	560

Tabulation of BrandedDummy logPrice\_mean when ATC is H01CB02

BrandedDummy	logPrice_mean		Total
	3.392117	6.507257	
0	1614	0	1614
1	0	127	127
Total	1614	127	1741

Tabulation of BrandedDummy logPrice\_mean when ATC is J01DB09

BrandedDummy	logPrice_mean		Total
	.9429331	2.306326	
0	1040	0	1040
1	0	123	123
Total	1040	123	1163

Tabulation of BrandedDummy logPrice\_mean when ATC is J01DH51

BrandedDummy	logPrice_mean		Total
	5.291308	5.694614	
0	915	0	915
1	0	62	62
Total	915	62	977



Tabulation of BrandedDummy logPrice\_mean when ATC is L01BA04

BrandedDummy	logPrice_mean		Total
	6.787386	7.66196	
0	922	0	922
1	0	239	239
Total	922	239	1161

Tabulation of BrandedDummy logPrice\_mean when ATC is M01AC05

BrandedDummy	logPrice_mean		Total
	1.121957	1.322568	
0	205	0	205
1	0	20	20
Total	205	20	225

Tabulation of BrandedDummy logPrice\_mean when ATC is M05BA02

BrandedDummy	logPrice_mean		Total
	3.482912	4.220175	
0	187	0	187
1	0	77	77
Total	187	77	264

Tabulation of BrandedDummy logPrice\_mean when ATC is N03AF01

BrandedDummy	logPrice_mean		Total
	.0180832	1.504435	
0	816	0	816
1	0	159	159
Total	816	159	975

Tabulation of BrandedDummy logPrice\_mean when ATC is N03AF02

BrandedDummy	logPrice_mean		Total
	1.82616	2.536251	
0	307	0	307
1	0	188	188
Total	307	188	495

Tabulation of BrandedDummy logPrice\_mean when ATC is N03AX14

BrandedDummy	logPrice_mean		Total
	2.775971	3.215427	
0	607	0	607
1	0	149	149
Total	607	149	756

Tabulation of BrandedDummy logPrice\_mean when ATC is N05AH03

BrandedDummy	logPrice_mean		Total
	2.291611	3.739169	
0	772	0	772
1	0	117	117
Total	772	117	889

Tabulation of BrandedDummy logPrice\_mean when ATC is N06AX21

BrandedDummy	logPrice_mean		Total
	2.513352	2.88979	
0	119	0	119
1	0	211	211
Total	119	211	330

Tabulation of BrandedDummy logPrice\_mean when ATC is R03DC03

BrandedDummy	logPrice_mean		Total
	1.8563	2.653926	
0	399	0	399
1	0	117	117
Total	399	117	516

Tabulation of BrandedDummy logPrice\_mean when ATC is R05CB06

BrandedDummy	logPrice_mean		Total
	3.606687	3.715805	
0	582	0	582
1	0	75	75
Total	582	75	657

Tabulation of BrandedDummy logPrice\_mean when ATC is S01AA27

BrandedDummy	logPrice_mean		Total
	.4890891	1.093453	
0	1710	0	1710
1	0	152	152
Total	1710	152	1862