More Weibo Use, Fewer Bad Drugs*

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Abstract

This paper examines how the introduction of Sina Weibo, the most popular microblog in china, helps improving the drug quality in the market. By exploring a drug quality data combined with a Sina Weibo use data as well as a moral hazard model, I develop three sets of results. First, the Difference-in-Difference estimate gives out an on average negative effect of the Weibo use on the number of the bad drugs found, while the dynamic effect finds the zero effects in the first couples of quarters but statistically significant negative effects since the fourth quarter after the introduction of Sina Weibo. It is an evidence for the coexistence of the screening effect and the discipline effect: when more information is revealed by Sina Weibo, more bad drugs are screened out, but at the same time, more monitoring disciplines the drug providers so that fewer bad drugs are provided and fewer bad drugs are found; the discipline effect will dominate and the number of the bad drugs found will decrease in Sina Weibo use when the use level is high. Secondly, the mechanism checks imply that Sina Weibo works through pushing the administrators working harder in drug checking and deterring the producers from producing the bad drugs. Finally, the heterogeneous effect shows that with the characteristic of low marginal delivery cost, Sina Weibo has higher marginal effect in some disadvantaged groups.

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1 Introduction

According to the World Health Organization's report (WHO, 2003), counterfeit drugs make up more than 10% of the global medicine market, and up to 25% of the drugs consumed in

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poor countries are counterfeit or substandard. Millions of people were killed by bad drugs each year, while the number for China is 200,000 to 300,000 people (Putze et al., 2012; Jia, 2007). How to combat the bad drugs has become an urgent and serious issue in developing countries.

This paper broadens the solutions by providing an evidence of the effect of media: Sina Weibo, the most popular microblog in China, can improve the drug quality in the market. The stubborn obstacle of the problem is to tell the drug quality. A healthy market and accountable governance is supposed to safeguard the drug quality, but unfortunately, they are often absent from many developing countries (WHO, FAQ; Torstensson & Pugatch, 2010). In this situation, the microblog can play a key role by delivering information to consumers and imposing pressure on regulators to drive out the bad drugs from the market.

Sina Weibo in China, a representative of microblog, can circulate the information among millions of users widely and quickly. Once a bad drug is found and revealed in Sina Weibo, the exponentially increasing followers and re-posts will spread out the information immediately and the informed consumers will stop buying the bad drug. The severer the problem, the more attention is called on. For example, when the 2010 vaccine scandal was revealed in Sina Weibo, a huge amount of posts flooded all over the China and thousands of parents called for an union in Sina Weibo to refuse having their children vaccinated by the official Disease Control Centers. Consequently, the problematic vaccine producers and related government regulators received their punishment.

To discuss the effect of Sina Weibo on the bad drugs in the market, a moral hazard model is developed. Given the number of the bad drugs provided, the more use of Sina Weibo and the more effort from the administrator, the more bad drugs are found. At the same time, more use of Sina Weibo brings more monitoring on the drug provider and fewer bad drugs are provided, so fewer bad drugs will be found out. The former is the screening effect and the latter is the discipline effect. The model predicts that the discipline effect dominates so that the number of the bad drugs found decreases in the Weibo use only when the Weibo use is high, although the number of the bad drugs provided always decreases in the Weibo use. There is also an effect on the administrator: the administrator will work harder when the Weibo use is higher, but the increase in the effort is smaller and smaller.

The empirical analysis combines a drug quality data from the China State Food and Drug Administration (SFDA) and a unique data of Sina Weibo measure from 2008 to 2011 to explore the effect of the Weibo use on the drug quality. Every quarter, SFDA imposes a uniform drug checking on around 85% of all Chinese prefectures, and the complete checking results are available since 2008. I use the number of the bad drugs found from the SFDA announcement to measure the drug quality, and the number of the drugs checked for the measure of the administrator effort. The drug data set covers the periods before and after the introduction of Sina Weibo. Sina Weibo becomes available since September 2009, and expands incredibly fast across times and regions. Such introduction creates large time and geographical variations in the Sina Weibo use, which are well measured by the data of Sina Weibo collected by Larsson et al (2012). The Weibo use is defined as the number of the Weibo posts including an emotionally neutral Chinese interjection word, *hei*, which has the high correlation with the total number of the Weibo posts (0.999) and the low appearance rate (0.0034). Both data sets are measured at prefecture by quarter level so that a good panel data is prepared for the empirical analysis.

Based on the assumption that the introduction of Sina Weibo is exogenous to the drug market, I use Difference-in-Difference identification to derive the causal effects. The introduction of Sina Weibo is an outcome of multiple factors. The number of cellphone users, the education expenditure and the tertiary industry GDP share are found to affect the growth of Weibo use. However, I find no correlation between the three factors and the number of the bad drugs found. Even including the interaction terms of the three baseline characteristics with the year dummies, the estimates are barely affected. It assures the DID strategy. There are, of course, other endogeneity concerns. I test whether the number of the bad drugs found predicts the introduction of Sina Weibo and the result rejects such reverse causality hypothesis. Substituting the Weibo use measure by the number of the newspapers, the estimate result excludes the concern that the effect of Sina Weibo is driven by the effect of the general media pressure. The placebo test that inserts pseudo event timings of the Weibo introduction and estimates using the data before Weibo enters also dismisses the possibility that some unobservable confounders pre-determine the trend of the bad drug issue and the introduction of Sina Weibo at the same time. The estimate of the effects are claimed to be causal.

The empirical results do find a huge effect of Sina Weibo. 1 percentage point increase in the Weibo posts decreases the number of the bad drugs found by around 0.1 percentage points, and the dynamic effect turns from zero to negative when the Weibo use increases to certain point. Both screening effect and the discipline effect of Sina Weibo existed. The effect is actually huge, which can be interpreted as, if every existed Weibo user increases 1 post every quarter, the drug quality will be improved by 1/3. The empirical analysis also finds that Sina Weibo works through pushing SFDA officers working harder and through deterring the producer from producing more bad drugs. The findings strongly suggest that microblog can be an efficient alternative to monitor the product quality and an extra strategy for consumers in developing countries that are bothered by the poor quality of products or services.

The study adds to a thin development literature that looks for effective ways in curbing the bad drugs. Björkman-Nyqvist et al. (2012) find that enhanced market competition can improve the drug quality: by exogenously increasing the amount of authentic drugs in the local market, fake drugs will be driven out. Other literature discusses the drug quality control from the regulation perspective (Oxfam, 2011). The solutions suggested above require the intervention from NGOs or governments, which might not be effective for countries facing the corrupt governments or dictators. The use of media, the microblog, might an alternative.

The essential characteristic of media is to provide and spread out information, which has an important role in shaping a healthy market (Akerlof, 1970; Shapiro, 1982). Existed literature focuses on the market price (Jensen, 2007; Svensson & Yanagizawa, 2009), but there is little literature about the effect of media on the product quality. So, the paper fills in the blank by providing empirical evidence that the use of Sina Weibo does reduce the number of bad drugs in the market.

A question arises from the Chinese context: can Sina Weibo survive the censorship and does the dictator really care about the social welfare. Besley and Prat (2006) argue that when the number of news outlets increases, silencing the media becomes more and more difficult. For Sina Weibo, each user can be regarded as a news outlet so it is difficult for the government to silence all of them. Furthermore, for the sake of regime solidity, the censorship executor - the central government is motivated to plan the social welfare and hold regulators accountable by removing poorly-performed ones (Besley and Masayuki, 2007). Hence, the Weibo posts about the bad drug issue can survive the censorship, even if some government corruption stories are involved. Although the theory about why the autocracy should care about the social welfare and the public opinions remains unclear and incomplete, it is empirically testable. A confirmative answer is provided by the study: SFDA is found to work harder in checking drugs where the Weibo use is higher.

Although the effect of media can make up market failure and governance failure, the access to media often diverts where the most benefit will go to (Prat and Strömberg, 2011). Direct evidence is Reinekka and Svensson (2005), who find that schools to which it was cheaper to deliver newspapers received more government funds. The new format of media, microblog, has low marginal delivery cost: as long as there is internet or smart phone, it is accessible. The paper checks the heterogeneous effects to see whether Sina Weibo will compensate for some ex ante disadvantaged groups. Regions with middle level of GDP per capita, regions with lowest education level, regions with middle level of the distance between market and producers are found to have higher marginal effect of Weibo use in terms of reducing number of bad drugs found in the market.

The paper is structured as follows. Section 2 describes the background of Sina Weibo and the bad drug issue in China. The model is developed in section 3. Section 4 presents the data and section 5 describes the econometrics method in use. Main results are reported in section 6, and the endogeneity concerns are addressed in section 7. Section 8 discussed the heterogeneous effects. Section 9 concludes.

2 Background

2.1 Sina Weibo

One month after Facebook and Twitter were banned by the Chinese government, a Chinese microblog - Sina Weibo launched its test version in Aug. 2009, and the official version in Sep. 2009. Sina Weibo is akin to a hybrid between Facebook and Twitter: it allows for at most 140 Chinese characters per post; Pictures and videos can be embedded; (private) message, comment and re-post are available; Weibo is accessible whenever there is an Internet or a smart phone, which are already widely used in China early as 2009.

With the convenient, friendly operation system and the prompt communicating way, Weibo quickly becomes the No. 1 popular microblog in China. By Feb. 2012, Sina Weibo has more than 300 million registered users (out of 1.3 billion Chinese population) and about 100 million messages posted per day[1]. The growth of Sina Weibo use is dramatically fast, in terms of both the use intensity and the geographical diffsion.

Before I show the statistics and graphs of the Weibo use growth, I first explain how the paper measures the Weibo use. The data of Weibo use comes from another of my coauthored project (Larsson, Qin, Strömberg & Wu, 2012). To measure the Weibo use, the number of total posts from each prefecture each day will be the ideal one. However, it is technically impossible to get such huge data set. We thus locate some emotionally neutral Chinese interjection words, which have the high correlation with total posts but the low rate of appearance. In the paper, The Chinese word used to construct the measure is *hei* (嘿), whose co-movement is 99.9% correlated with the total number of the posts but the appearance rate is only 0.0034. Then we download all the posts including the word *hei*, which finally give out the measurement in the paper: the number of Weibo posts including the word *hei* in the prefecture and the quarter.

Table 1 shows how Weibo grows across time. By this measure, only 45 prefectures introduce Weibo in the first possible quarter, and only one year later, around 309 prefectures (around 90% of the total number) have Weibo entered. The mean number of posts including *hei* increases from 2.5 to 96.6 in two years, and the standard deviation is as large as 2-3 times of the mean in each quarter that suggests the big variation across regions.

Figure 1 gives out the distribution of Weibo use across regions and across years. The regional differentiation in terms of economy development is salient in China: southeast coast cities are much richer than the northwest cities. However, it is difficult to conclude that Weibo use concentrates in either part of China.

The introduction of Sina Weibo is an outcome of multiple factors, including economical and social factors. The economy condition matters only for the entry cost for access to

[1] According to SINA Corporation

Weibo: internet or smart phone. Once this requirement is satisfied, the marginal cost is almost zero. The internet has finished the rolling down all over the whole China in 2007 and smart phones are widely used in 2009. Except for really poor prefectures that have very low level of internet and smart phone use, access to Sina Weibo is not difficult. Even with similar economy development level, people may have different preference for cellphones: cities that are more fancy, have higher share of younger generation, or enjoy more from sharing, tend to use more smart phones. Compared with the growth of smartphone users, Sina Weibo spreads out much faster. Therefore, regions with more smartphone users experienced a sharp jump in using Sina Weibo than others when Sina Weibo became available. The ability and the preference of writing are other factors influencing the use of Sina Weibo: people with more education tend to write more and thus might write more Weibo posts either. The share of different occupation types matters in the sense that people with more flexible working schedules are more likely to check and post on Sina Weibo time and time again. The local culture also matters a lot, because cities that have strong preference in communication and social life tend to use more Sina Weibo. In sum, there are many factors interacting with each other and influencing Weibo use at the same time, so it is not likely that the introduction of Sina Weibo is strongly correlated with the drug market needs by itself. It lends the support to the identification strategy this paper uses. More detailed econometric checks and tests will be discussed in section 5 and section 7.

Sina Weibo can become an efficient monitoring alternative to drug quality in the market. Topics in Weibo vary from daily life to international political events, and users vary from big names to ordinary people etc. The drug issue is one of the popular topics in Weibo: according to the searching word ranking by Sina Weibo in Aug. 2012, “Vitamin” ranked No. 2 and “OTC” (over-the-counter, non-prescription drugs) ranked No.9 in the category of “life”. When people encounter or hear some bad drug problems or stories, they can post in Sina Weibo and immediately reveal the stores or producers who provide the bad drugs. Given the high attention on the drug issue, such posts will be quickly spreading out by the followers and re-posts. The potential consumers will then stop buying such bad drugs, while the administrator will go and check the bad drug providers.

People may question that Sina Weibo will be silent by the notorious censorship system in China, when it talks about the bad drugs, especially scandals that have the government corruption issue involved in. It is true that Sina Weibo is subjected to the censorship, but it does disseminate the bad drug stories, even the scandal type, widely. Information spreads out very quickly in Sina Weibo especially when there are many users. Millions of users might have read the post before it is deleted. Besides it, there are another two reasons to believe Weibo does work.

(1) The censorship is mainly applied to issues sensitive to party regime or political reforms, and the bad drug issue is not one of them. Issues that are related with the daily life and

local offices' corruption are actually less censored. The Chinese central government is the one implementing the censorship. For the sake of maintaining the overall solid governance, the central government is also motivated to monitor the local government's performance and crack down corrupt officers. However, it is undeniable that the central government still can and might censor some news/comments in Sina Weibo related with the bad drug issue. In this case, the skill of circumvent is used.

(2) By the Chinese language characteristics, circumvent of the censorship is easy in internet. Censorship is implemented by filtering the sensitive key words. In China, netizens use words with similar pronunciation but totally different characters to deliver the same meaning so that the post will not be sent to the censoring server. For example, "harmonize/harmonization", originally a highlighted word from the Party report, is now a word that people use to refer to the government censorship in the sarcastic sense, A post including the word nowadays will be sent to the censoring server, so netizens now use "river crab" which has the similar pronunciation but totally different Chinese characters to substitute it.

Therefore, in spite of the censorship, all kinds of news/comments, even ones that the government does not like, are widely circulated across the whole China. Sina Weibo is regarded as the freest media in mainland China. Whether Sina Weibo will have effect on both people's life and government's accountability in China is an empirical question the paper tries to answer.

2.2 Bad drugs problem in China

The bad drug in the paper is defined as counterfeit or substandard drugs. A drug can become bad when it is produced due to the unqualified production, or when it is distributed due to the inappropriate delivering or storage.

China has become one of the biggest pharmaceutical producers and one of the biggest bad drug producers. In 2010, the annual growth rate of Chinese pharmaceutical industry has amounted to around 17% and the total output amounted to $240 billion. [2] However, at the same time, China not only confronts a significant presence of bad medicines in the domestic market but also is list as one of the world's largest producers of substandard and counterfeit medicines. (Christian et al., 2012)

Corruption is the most frequently cited reason that contributes to the severe bad drug problem in China (Christian et al., 2012; Torstensson and Pugatch, 2010). The State Food and Drug Administration is the national regulatory and enforcement agency that oversees all drug manufacturing, trade and registration. Under the national level, there are provincial and prefecture level FDAs, which actually carry out the daily monitoring and enforcement jobs. From central to local FDAs, corruption problems are serious. For example, in 2007, the

[2]Figures come from the National Development and Reform Commission.

former director of the SFDA, Zheng xiaoyu was executed for taking bribes to approve fake medicines. In 2007 and 2010 vaccine scandals, couples of provincial governments are found guilty by allowing unqualified vaccine flow into the disease control centers where children take vaccines.

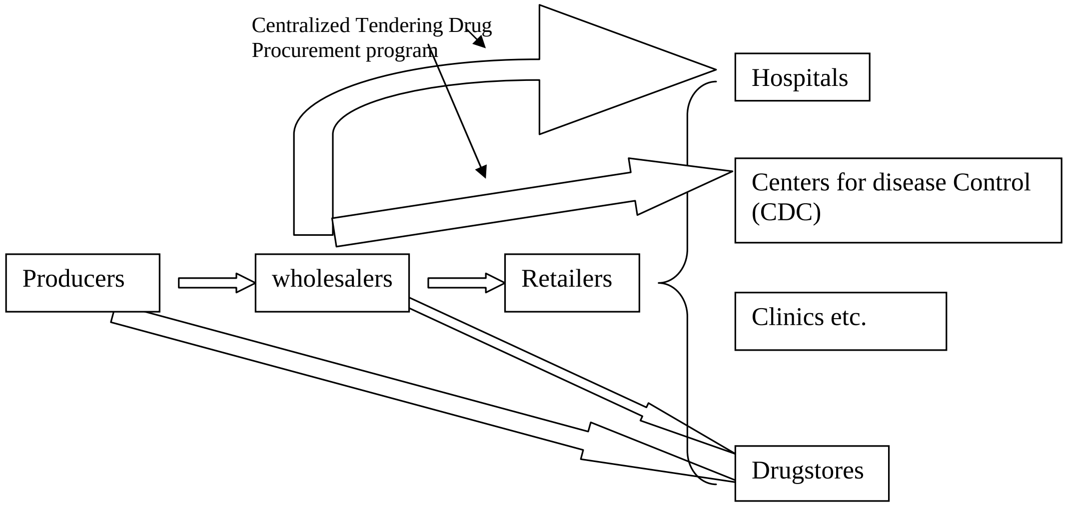
Besides corruption, the characteristic of Chinese pharmaceutical industry and the administration system is another important reason that accounts for the bad drug issue in China. The domestic pharmaceutical market is highly fragmented: by 2010, there are 7039 domestic pharmaceutical manufacturers[3] and more than 13,000 distributors (Atkearney, 2011). Thousands of domestic pharmaceutical companies account for 70% of the market, while most of the manufacturers are small producers of generic drugs and vary a lot in the quality (Sun et. al, 2008).

The process from the time when drugs are produced to the time when drugs are delivered to consumers is very long and complicated in China. The bad drug issue deteriorates in such process. Because most of drug producers in China are with small size and not qualified for the specific drug delivery requirements, there are usually some wholesalers between drug producers and drug retailers. For the retailers, there are four types: hospitals, centers for disease control, clinics or similar small health service centers, drugstores. Among them, hospitals remain as the dominant selling channels, accounting for 70% of all drugs sold; while drugstores are the next. Prescription drugs are mainly allowed to sell in hospitals and only limited numbers of drugstores are permitted to sell them. In China, drugstores distribute mainly the over-the-counter (OTC) drugs.

The graph below explains how drugs are distributed in China. The Centralized Tendering Drug Procurement Program (CTDP) imposed by the central government actually makes the drug distribution process prolonged and complicated, which can cause drugs rotten in any point of the chain, either by nature reasons or by human reasons.The initial purpose of using CTDP is to control for the health expenditure and regulate the drug market. In China, public health institutes can only purchase drugs from the wholesalers who won the bid in CTDP and other health service institutes (non-public clinics and drugstores) are encouraged to (but not have to) use the system. CTDP does not test the quality of the drugs that are circulated via it, but it does check the certificates associated with all drug providers that are involved in. If all health services use CTDP, theoretically, the counterfeit drugs can be considerably reduced in the market. However, CTDP is operated by some government offices and turns out to be a complicated and costly system. Hence, not only drugstores but also some small hospitals and clinics do skip the system and go directly to the producers (Dong et al. 1999). Small retailers have limited capability in drug evaluating and shipping, bad drugs happen in these purchase ways.

[3]The Chinese High-tech Industry Statistics Yearbook 2011.

Drug distribution in China



From the perspective of administration system, two aspects contribute to the bad drug issue in China.

(1) Exempting from the inspection system. According to the rule, pharmaceutical enterprises can apply for the exemption of regular inspection if their products passed the first several products inspection from FDAs. Pharmaceutical industry is one of the high tax generators for local governments so it is common to see local officers help pharmaceutical manufacturers to obtain the exemption. Additionally, in lack of the accountability, FDAs do not mind work less. Hence, huge amount of pharmaceutical enterprises have obtained the exemption in China. It turns out that many bad drug stories revealed by the media these years are often related with these firms.

(2) Considerably many small drug producers and distributors in China make it difficult for a single regulatory agency to control effectively. Furthermore, the daily monitoring is the job of local FDAs, but it is pointed out that the pay of local leaders is too low to motivate them to enforce drug regulation standards (Christian et al., 2012).

Although the central government has put lots of effort in combating the bad drug problems, the achievement is small. Given the development level of domestic pharmaceutical industry and the questionable governance, more monitoring method is needed to improve the drug quality in the market. The new and popular media, Sina Weibo, is such a possible alternative.

2.3 Attention is the power, and circusee is changing China

The subtitle is the words that Chinese people use to describe the contribution of Sina Weibo. The word “circusee” composes of two, “circus” and “see”, which refers to the power of Weibo that makes millions of people to look on one issue together. As the introduction of Sina Weibo makes the instant communication possible to cross the geographical borders and the voice of most people to be heard, it does help China with the bad drug problem. Hereby, I give out two stories to exemplify the big effect of Sina Weibo on the bad drug issue.

Case 1 : 2010 Problematic Vaccine Scandal.

March 17, 2010, a famous journalist, Keqin Wang published an article on newspaper *China Economic Times*, and Sina Weibo, “An Investigation into Vaccinations that Went Horribly Wrong”. Additionally, he also published more concrete and detailed evidences in Sina Weibo. The report pointed out that hundreds of children in Shanxi province were affected with strange illnesses or died because of the vaccine they were injected in 2007. The report immediately shocked the whole Chinese society.

Although the State Information Office had ordered the deletion of the *China Economic Times story*, and the Central Propaganda Department issued a directive instructing traditional media to use only official releases from Xinhua News Agency the day after the report came out, the reports and comments were still widely spreading in Sina Weibo. Following the exposure of Shanxi Vaccine scandal, similar cases that illnesses were caused by the problematic vaccine in other provinces were subsequently revealed. Furious parents all over the country strongly appealed to the government for investigation of the vaccine scandals[4]. Many parents even refused to have their children vaccinated. By March 29, directors, vice directors of the Center for Drug Evaluation and the Center for Certification of Drug within SFDA were replaced, and many officers from SFDA and Shanxi provincial FDA were arrested for investigation. The central government also sent a team of experts to Shanxi to investigate the vaccine scandal, and most of provinces initiated their own checking on the vaccines.

The Shanxi scandal revealed in 2010, however, was not just out in 2010. Actually as early in 2007, the Court in Taiyuan, the capital city of Shanxi province, already received several lawsuits on the problematic vaccine that caused children sick; couple of newspapers and TV channels also reported the possible vaccine scandal. Shanxi provincial health department promised to check but ended up with the answer as: the vaccines that were used are qualified and no guilty is found to any officer.

The successful cracking down on the problematic vaccines in 2010 but failure in 2007 was mainly owed to the widely circulated reports that attracted extremely large attention from the public in 2010. During the process, Sina Weibo played an important role in dispersing the reports and discussions. In this sense, by the end of 2010, Chinese use the words to describe Sina Weibo, “Attention is the power, and circusee is changing China”.

[4]All vaccines are ordered, distributed and injected by the government offices in China, the Centers for Disease Control and Prevention.

Case 2: 2012 Poison Capsule Scandal

Besides calling for immediate huge attention from the public after a scandal is revealed, Weibo can also urge scandals to be revealed. "Poison Capsule Scandal" is a good example.

On April 9, 2012, a famous China Central Television (CCTV) presenter, a journalist and a famous internet speaker all posted on their Sina Weibo to implicitly or explicitly point out that industrial gelatin is added into some yogurt and jelly products. Immediately, countless discussion posts were flooding in the internet. Officers from the Confectionery Committee of China National Food Industry Association claimed to reserve the right to suit the presenter. Some anecdote story told that the CCTV presenter was then shut out by the government and in this scenario, CCTV was actually forced to air an investigation video on April 15, 2012. The video suggested that 13 commonly used drugs from nine pharmaceutical companies were found to be packed into capsules that were made from industrial gelatin retrieved from waste leather materials, which contains excessive chromium.

The Chinese government reacted very promptly this time. On the same day of the broadcast of the poison capsule scandal in CCTV, SFDA issued an emergency notice to suspend the selling and consumption of the 13 drugs in question. Since April 19, the Ministry of Public Security initiated a big cracking down campaign all over the whole country: hundreds of drug producers were checked and hundreds of people who were found as guilty in the scandal were arrested, and only in one week over 77 million of problematic capsules were forfeited.

Since the poison capsule scandal, the discussion on the weak governance continues heating the headlines in all kinds of medias for a long while. On June 2nd, one and half month after, I search the key word "questionable capsule" in Weibo: in total 1,171,810 posts are list out.

Undeniable, microblog can be a strong candidate for drug quality monitoring.

3 Mechanism

Before running to the empirical part, a theoretical framework about how Sina Weibo affects the drug quality in the market is discussed in the section. Based on Holmstrom (1979, 1999), Prat and Stromberg (2011), I build a simple two period moral hazard model to explain the mechanism. In the model, there is a drug provider, an administrator, and consumers who cannot observe the drug quality but receive information either from the administrator or the media, Sina Weibo. Both the drug provider and the administrator can be kicked out of the market/office in the end of first period, if they are found out as bad or irresponsible. Although the issue addressed in the paper is under autocracy and there is no such voting mechanism to hold the government accountable, the governor still have motivation to replace the irresponsible regulator/bureaucrat because they care about the consolidation of the governance and thus the reputation, which can be weakened by government scandals revealed. The aim of the model is to disentangle the different effects of Weibo on the administrator and the provider, and to describe how the Weibo use affects the drug quality in the market. Some hypotheses are derived from the model for empirical tests.

Basic setting

In period 1, an exogenously selected provider supplies the whole market with amount 1, and consumers decide whether they want to change the provider in the end of first period according to the information from the administrator or Sina Weibo. Assume there is no discounting.

There are two possible types of providers, $\theta \in \{g, b\}$, where g refers to "good" and b refers to "bad". The provider is type g with probability $Pr(\theta = g) = \gamma \in (0, 1)$. The provider can choose providing bad drugs $x \in [0, 1]$ or good drugs, $1 - x$. The type b provider benefits linearly from providing bad drugs $\Pi^b = x$, but for every amount of bad drug provided, a signal of that the provider is the bad type will be sent out, $S(x) \in [0, 1]$. The type g provider benefits zero from providing bad drugs and always provides good drugs $x = 0$, $\Pi^g = 1$, so no signal is sent out, $S(0) = 0$. In the reality, some providers are associated with advance equipments and technologies, so the cost of providing good drugs for them is such low that it is not worth to risk providing bad drugs at all. These are good providers. Some providers are poorly equipped and using backward technologies, and it is very costly for them to provide good drugs. Hence, the bad provider can benefit from providing bad drugs only. I further assume that the signal is a convex function on x , $S' > 0$, $S'' > 0$: the more bad drugs provided, even more signal that the provider is b will be sent. If all drugs provided are bad, the signal will be $S(1) = 1$, the provider is found out as bad type for sure. I also assume $S'(0) = 0$ and $\lim_{x \to 1} S'(x) = \infty$.

Consumers can only benefit from good drugs, $1 - x$, but cannot observe the drug quality at the time of selection. Consumers collect information about the provider type from either the administrator or Sina Weibo, and I assume $\lambda \in (0, 1)$ portion of consumers get information from the administrator while the left $1 - \lambda$use Sina Weibo to get the information.

Suppose Sina Weibo catches the signal $S(x)$ with probability $w \in [0.1]$. Here w also stands for the intensity of Weibo use: the more Weibo use, the higher probability that the signal is caught by at least one of the Weibo users and then revealed in Weibo. As I discuss in section 2, it is difficult to impose the censorship on Weibo and the marginal cost to report in Weibo is very low, so it is reasonable to assume Weibo always reports the signal if it perceives. Hence, Sina Weibo catches the signal of that the provider is b type with probability $S(x)w$.

An exogenously selected administrator is in the office in the first period and works with effort $e \in [0, 1]$ to catch the signal, and then she catches the signal that the provider is type

b with probability $S(x)e$. The administrator benefits from being in power, receives A if in power, and suffers from every effort she pays by e^2. The administrator will lose the job in the end of period 1 if she fails to catch the signal that is caught by Sina Weibo, i.e., with probability $(1-e)S(x)w$. The assumption is realistic since we do observe in the reality that, when some scandals were revealed by Sina Weibo, the corresponding officers, who were supposed to regulate it but did not, were dismissed from the office.

As a whole, consumers believe that the current provider is type b and replace her in the end of first period with probability $\lambda S(x)e + (1-\lambda)S(x)w$. Therefore, the probability that the type b provider is found and replaced depends on the amount of bad drugs she produces, x, the administrator effort e and the intensity of Weibo use w. That is

$$P_{found} = \lambda S(x)e + (1-\lambda)S(x)w$$

where P_{found} also refers to the amount of bad drugs were found out and revealed to consumers: the more bad drugs were revealed, the higher probability the provider is believed as type b and kicked out of the market. If the current provider is kicked off, another provider will be randomly selected from the pool, still with γ probability to be good.

In period 2, if the provider is type b , without motivation to maintain in the market, she will provide all bad drugs in the second period $x = 1$.

Administrator problem

In the second period, the administrator would not work $e = 0$ and recieves the benefit A . However, in the first period, she works with the effort level that at least can maintain her in the power till the second period. The administrator chooses e in the first period to solve the following problem

$$\max_{e} A - e^2 + A[1-(1-e)S(\hat{x})w]$$

$$\Longrightarrow \text{the optimal } \hat{e} \text{ satisfies } \hat{e} = \frac{1}{2}AS(\hat{x})w$$

where $\hat{x}$ is the given bad drugs that are provided in the market. The first order condition then gives out $\frac{d\hat{e}}{dw} = \frac{1}{2}AS(\hat{x}) \geq 0$. The administrator works harder if the level of Weibo use is higher, but the marginal increase might not be maintained all the time. The second order derivative is $\frac{d\hat{e}}{dwdw} = \frac{1}{2}AS'(\hat{x})\frac{d\hat{x}}{dw}$, which is negative if $\frac{d\hat{x}}{dw} < 0$. I will prove the negative sign later.

Provider problem

If the provider is type b in the first period, she chooses x with the consideration of the trade-off between benefit form bad drugs and the probability of maintaining in the market till the second period. The more bad drugs she provides, the higher probability she will be found as bad type either by the administrator or by Sina Weibo.

The provider knows how the administrator works, which appears to her as $e = e(w)$ and $e'(w) \geq 0$. The type b provider chooses x in the first period to maximize

$$\max_{x} x + 1 - (\lambda S(x)\hat{e}(w) + (1-\lambda)S(x)w)$$

$$\Longrightarrow \text{optimal } \hat{x} \text{ satisfies } S'(\hat{x})(\lambda\hat{e}(w) + (1-\lambda)w) = 1$$

where the left hand is the marginal cost of providing bad drugs due to the stronger signal that the provider is type b, and the right hand side is the marginal benefit from providing bad drugs. The first order condition further gives out,

$$\frac{d\hat{x}}{de} = -\frac{S'(\hat{x})\lambda}{S''(\hat{x})} < 0$$

$$\frac{d\hat{x}}{dw} = -\frac{S'(\hat{x})(\lambda\hat{e}' + 1 - \lambda)}{S''(\hat{x})(\lambda\hat{e}(w) + (1-\lambda)w)} < 0$$

The amount of bad drugs provided, x, is decreasing in the administrator's effort e and is decreasing in w, the intensity of Weibo use. However, the effect of w on the amount of bad drugs found, which is also the probability for b to be regarded as type b, is ambiguous.

$$w\uparrow \Longrightarrow \left\{ \begin{array}{l} \uparrow e, \uparrow w \Rightarrow \uparrow \lambda S(\hat{x})e(w) + (1-\lambda)S(x)w \text{ given } \hat{x} \\ \downarrow \hat{x} \Rightarrow \downarrow \lambda S(\hat{x})e(w) + (1-\lambda)S(x)w \end{array} \right.$$

Holding the amount of bad drugs provided fixed, the more Weibo use, the more bad drugs are revealed by Weibo; the more Weibo use, the harder the administrator works, and thus the more bad drugs are revealed by the administrator. This is the screening effect of Weibo. However, where there is more Weibo use and more effort from the administrator, providers tend to to provide fewer bad drugs, so fewer bad drugs can be found out and the provider is less likely to be changed. This is the discipline effect. The two effects have opposite direction so the net effect of w on $P_{found}$is ambiguous, which can also be seen from the following equation

$$\frac{dP_{found}}{dw} = S(\hat{x})(\lambda\hat{e}' + 1 - \lambda) + S'(\hat{x})(\lambda\hat{e}(w) + (1-\lambda)w)\frac{d\hat{x}}{dw}$$

The first part refers to the screening effec, and the second part represents for the discipline effec. The sign of the derivative depends on the level of w . The amount of bad drugs found is expected to be decreasing on w only when w is high. When w starts with a low level, an increase in w will cause huge screening effects, which will beat the discipline effects and the net effect will be positive on P_{found}. It is because $\lim_{w\to 0+} P_{found}(0) = 0$. and

$\lim_{w\to 0+}\frac{dP_{found}}{dw}>0$

$$\begin{aligned}\lim_{w\to 0+}\frac{dP_{found}}{dw} &= \lim_{w\to 0+}S(\hat{x}(w))(\lambda e'+1-\lambda)+\lim_{w\to 0}S'(\hat{x}(w))(\lambda\hat{e}(w)+(1-\lambda)w)\frac{d\hat{x}}{dw}\\ &= (\lambda e'+1-\lambda)(\lim_{w\to 0+}S(\hat{x}(w))-\lim_{w\to 0+}\frac{(S'(\hat{x}(w)))^2}{S''(\hat{x}(w))})\end{aligned}$$

where $\lim_{w\to 0+}\hat{x}(w)=1$, so $\lim_{w\to 0+}S(\hat{x}(w))=1$. $\lim_{w\to 0+}\frac{(S'(\hat{x}(w)))^2}{S''(\hat{x}(w))}=0$. Hence $\lim_{w\to 0+}\frac{dP_{found}}{dw}=\lambda e'+1-\lambda>0$.

Now let's go back to the administrator's problem, we know that $\frac{d\hat{e}}{dw}\geq 0$, but the effort does not increase with w all the time. It is because $\frac{d\hat{x}}{dw}<0$. So $\hat{e}''(w)=\frac{d\hat{e}}{dwdw}=\frac{1}{2}AS'(\hat{x})\frac{d\hat{x}}{dw}<0$

It suggests that the increased effort caused by the increase of Weibo use $\frac{d\hat{e}}{dw}$ will decrease with the increase of Weibo use w, and drop towards zero.

Consumer's Welfare

Although, the effect of w on amount of bad drugs found is ambiguous, the consumer's welfare is always increasing in w. Consumers only care about the real drugs they consumed, and the welfare function is given by the following equation:

$$V(x;w)=2\gamma+(1-\gamma)[1-\hat{x}+(\lambda S(\hat{x})\hat{e}(w)+(1-\lambda)S(\hat{x})w)\gamma]$$

The first part of the equation is the welfare for consumers when type g provider is selected in the first period, and the second part is the welfare if instead type b provider is selected in the first period. The type b provider provides $\hat{x}$ in the first period, leaves $1-\hat{x}$to consumers, and thus generates probability $\lambda S(\hat{x})\hat{e}+(1-\lambda)S(\hat{x})w$ of being replaced by another provider, who has probability of γas good type. By the Envelope Theorem, we have

$$\frac{dV}{dw}=(1-\gamma)S(\hat{x})(\hat{e}'(w)+1-\lambda)\gamma>0$$

It is easy to see that under the assumption that when the administrator reacts to the Weibo use, the consumer's welfare is better off than if the administrator does not, i.e. $\hat{e}'=0$.

Hypotheses and test:

In sum, the moral hazard model gets:

Proposition 1: The amount of bad drugs provided in the market is decreasing in Weibo use, $\frac{d\hat{x}}{dw}<0$. The amount of bad drugs found out is affected ambiguously by Weibo use because of the coexistence of screening effect and discipline effect, $\frac{dP_{found}}{dw}=S(\hat{x})(\lambda\hat{e}'+1-\lambda)+S'(\hat{x})(\lambda\hat{e}(w)+(1-\lambda)w)\frac{d\hat{x}}{dw}$. The amount of the bad drugs found is decreasing in the Weibo use w only when w is high.

Proposition 2: The administrator works harder when there is higher Weibo use, but the increase of the effort decreases in Weibo use. $\hat{e}'(w) \geq 0$, $\hat{e}''(w) < 0$. The number of bad drugs provided in the market also decreases in the administrator's effort, $\frac{d\hat{x}}{de} < 0$.

Corollary 1: The consumer's welfare is increasing in the Weibo use $\frac{dV}{dw} > 0$, and consumers are better off if the administrator reacts to Sina Weibo, i.e. if $\hat{e}'(w) > 0$.

The prediction of the model composes of two separable parts: proposition 1 is the aggregated market outcome, which is established regardless of whether proposition 2 established or not; proposition 2 is the effect of Weibo use on the regulator, which strengthens the effect of the Weibo use on the market outcome.

I summarize the main prediction of the model in figure 2. When the Weibo use increases, the number of bad drugs provided in the market decreases, while the number of bad drugs found can be increasing first and then definitely decreasing after certain amount of the Weibo use is achieved. The administrator effort increases with the Weibo use but the increase becomes smaller and smaller. The number of bad drugs provided, $\hat{x}$, is not observable, and then $\frac{d\hat{x}}{dw} < 0$ is not directly testable. The relationship between the Weibo use and the number of bad drugs found and the relationship between Weibo use and the administrator effort are the main hypotheses the following sections will test.

The study tests the prediction using a measure of the Weibo use for w, and the number of bad drugs found in the market as P_{found}, as well as the total number of drugs checked as a proxy for the administrator effort e. (More details about the data is discussed in Section 4) According to proposition 1, $\frac{dP_{found}}{dw}$ can only be negative when the level of Weibo use is high. The level of Weibo use increases over time after its introduction and the estimate of the net effect of Weibo use using the panel data can be either negative or positive, depending on the average level of Weibo use in the data period. If there are long enough time periods for Weibo use to grow, the discipline effect will dominate since certain point and then we can observe the negative sign for the aggregated effect estimate. And if the turning point does show up among the dynamic effects, it definitely suggests both effects existed, because the sign of the effect estimate would not change if only one of them existed.

Similarly, I examine the relationship between the administrator effort and the Weibo use by exploring the dynamic effect of Weibo use. Proposition 2 is actually based on an implicit assumption that the governor do care about the bad drug issue and will replace the regulator if she fail to fulfill her job. Although the reasoning why an autocracy cares about the social welfare and the bad drug issue is theoretically not explained comprehensively by the literature, whether the assumption holds or not becomes am empirical question in the paper. If the proposition 2 is true, the estimate of the marginal effect of the Weibo use on the administrator effort should be positive in the beginning but the magnitude should be decreasing over times towards zero. Under the model setting, if the amount of bad drugs found turns out to be decreasing in the Weibo use and the administrator effort is also increasing in the Weibo use, I can derive the conclusion that the number of bad drugs provided in the market is decreasing in the Weibo use.

There is only one provider in the model, but in the real world, drug providers consist of two separated parts: producers and distributors. Drugs can become bad either because of producers or distributors. Sina Weibo may play the monitoring role to both the retailer in where the drug is sold and the producer in where the drug is produced. The number of bad drugs found discussed in the main part of the empirical analysis refers to the bad drugs found in any point of the distribution process, so it does differentiate the reasons that deteriorate the drug. To shed a light on the mechanism of the effect of Sina Weibo, I also use the producer information of each drug in check to test whether there is a discipline effect on the drug producer.

When both screening effect and discipline effects are proved to be existed, and the administrator works harder with higher Weibo use, corollary 1 is then derived: the consumer's welfare is better off with higher Weibo use.

4 Data

I explore the drug quality using the data from quarterly published *the National Drug Quality Announcement* by the State Food and Drug Administration[5] from 2008 to 2011, including 16 quarters, 43726 drugs from 317 prefectures. The bad drugs are drugs found unqualified by SFDA, including counterfeit and substandard drugs. Collapsing the data at prefecture by quarter level, I get the number of the bad drugs found in each prefecture at the quarter as the index for P_{found}, and the number of the drugs checked as the index for the administrator effort e. Since the number of bad drugs found in the model, P_{found} , includes both the bad drugs revealed by the administrator and the ones by Sina Weibo, is it appropriate to use the bad drugs announced by SFDA as an index for P_{found}? Although these bad drugs are announced by SFDA, not all of them are found out by SFDA's effort, and if some bad drugs have been exposed by Sina Weibo, SFDA will directly go and catch it without any effort. In this sense, using the data of the bad drugs announced by SFDA is justified. The number

The National drug quality announcement is the report of the quarterly drug check implemented by SFDA. SFDA samples the specific drugs from around 300 (out of total 340) prefectures every quarter and then send them to test. About two months after the check, the report of the result - the *National drug quality announcement* is published on the website of SFDA. The announcement includes the record of every drug they checked: drug name,

[5]http://www.sfda.gov.cn/

producer, sample source where drugs are sampled, test result etc. (A piece of record from the table is cut and list in the appendix, figure A). I code the prefecture information according to the sample source (when studying the drug quality in the market) and producer names (when investigating the drug quality in production). The report does not specify whether the drug fails to be qualified is due to production or inappropriate storage/shipping. Therefore, the analysis, unfortunately, is not able to further discover the heterogeneous effect of Weibo use on reducing the misbehavior of producers and of distributors.

The quarterly drug check from SFDA is comprehensive and representative so that the result announcement turns out to be a good data for analyzing the drug quality in China. From production to distribution, all types of drug providers are sampled, including six categories - (1) clinics, (2) disease control and prevention center/anti-epidemic stations and such offices under the Health department, (3) drugstores (4) hospitals. (5) wholesalers/intermediary drug companies and (6) producers. The distribution of the sample sources is proportional to the number of the providers in the market (A summary of source type distribution for full sample and bad drug sub-sample is list in appendix Table A.). Among the retailers, the bad drug rate is overrepresented in the drugstores. The fact is consistent with the phenomenon that many drugstores in China have small size, and many of them are privately owned, which makes the monitoring from FDAs more difficult. SFDA's checking list, according to the Rules[6], contains the most widely used drugs, the drugs that were reported with severe adverse drug reaction, the drugs that were ever found unqualified in the past etc. The drugs on the list can be the traditional Chinese medicine, synthetic drugs or biotech-related drugs (Table B in appendix gives the summary of the categories of drugs in check, while the synthetic drugs are the main part in check and are further categorized into sub-groups[7]). In the sample years, in total 21 categories of drug types are checked; among them, the most overrepresented bad drug is the non-immunization, other biotech-related drugs, which is fragile during the distribution as in the production.

To give a rough idea of the bad drug distribution across regions, figure 3 plots the yearly number of bad drugs found per million people in the map, at prefecture level. From figure 3, we can see that the bad drugs actually do not concentrate in certain regions: it is hard to conclude that the bad drugs are more likely to be found in east or west, south or north of China.

The measure of the Weibo use, the total number of the posts including Chinese character *hei* by prefecture and quarter (described in section 2) covers 340 prefectures and 9 quarters[8].

[6]About the sampling rules and checking scheme, please refer to http://www.gov.cn/gongbao/content/2003/content_62323.htm

[7]I categorize the drugs according to the method SFDA used for Essential Drug list. http://www.moh.gov.cn/publicfiles/business/htmlfiles/mohywzc/s3580/200908/42506.htm

[8]SinaWeibo began available since Sep. 2009 and the time period in the paper is quarter, I thus take the last quarter of 2009 as my first observation of Weibo use.

Population of each prefecture is used to scale the measure for the regression use. The introduction of Sina Weibo is not driven by one single factor: its distribution is not coincident with GDP per capita, and more importantly, not coincident with possible factors that may influence the drug market, pharmaceutical industry distribution and medical needs (proxy by the hospital beds per 10,000 people). Figure 1 graphically compares the distribution of the Weibo use measure with the GDP per capita, the pharmaceutical industry product value and the hospital beds. It is hardly to tell there is any similarity between any year of the Weibo use and the three concerned factors. Empirical evidence about the determination of the Weibo introduction is shown in section 5.

The Data of prefecture characteristics come from the China City Statistically Yearbook 2009-2011, which are referred to 2008-2010 statistics[9]. Variables in use include population, GDP per capita, the number of Internet users per 10,000 people, the number of cellphone users per 10,000 people, the number of hospital beds per 10,000 people, education expenditure per capita and so on.

Merging all the data sets mentioned above, I get the data set used in the analysis, which contains 2977 observations from 290 prefectures and 16 quarters. Among the 290 prefectures, 7 of them have no Weibo entered in all the sample quarters. A summary of statistics is given by table 2. We can see that 43% of prefectures are ever found with bad drugs, while for each quarter there are, on average, 5% of the prefectures are found with bad drugs. The average number of bad drugs is 0.065 but the average population of the prefecture is around 4 million, so I weight the number of bad drugs found by million people.

Two points I want to emphasize here: the Weibo use measure is not exactly the same number of total Weibo posts from the prefecture by the time. When we observe the Weibo use measure as zero, it does not mean there is no Weibo post from the prefecture at all, but it definitely means Sina Weibo has not gained the minimum popularity to be shown by the index. And the Weibo posts we count are the posts about anything, and have nothing specific to do with the drug market issue. For the convenience reason, the paper refers the term of "Weibo enters" as the Weibo use measure turns into positive.

5 Econometric model

The study aims to estimate the causal effect of the Weibo use on the drug quality in the market. As Sina Weibo became available only since Sep. 2009, later than the time when SFDA started the drug quality check[10], it suggests a perfect chance to use Difference-in -Difference as the identification. Figure 4 gives a rough idea of why the Difference-in-Difference identification

[9]Without 2011 statistic information at hand, I duplicate 2010 population statistics for 2011

[10]SFDA start the quarterly checking since 2003, but complete data available online only since 2008.

is applied. Both graphs show the relationship between the number of bad drugs found[11] and the timing of the Weibo introduction. X axis labeled as 0 refers to the first quarter that Sina Weibo enters, 1 as one quarter after Weibo enters while -1 refers to one quarter before.[12] Y axis represents the level of bad drugs found: the upper panel uses the raw data of the number of bad drugs found while the bottom panel uses the number of bad drugs found that gets rid of the prefecture fixed effects, quarter fixed effects, and the prefecture specific time trend. Both graphs give out similar implication: after Weibo enters, there is a clear declining trend for the number of bad drugs found. So it is reasonable to use the timing of Weibo introduction as the identification.

Furthermore, as the prefectures pick up Weibo staggeringly, the intensity of the Weibo use varies across regions in each quarter. I then use the time varied and regional varied Weibo use measure to estimate the impact on the number of the bad drugs found, fitting the following equation:

$$P_{found\_it} = \eta \ln pop_{it} + \beta W_{it} + \alpha_i + \lambda_t + \alpha_i * t + \theta X_{it} + \varepsilon_{it} \quad (1)$$

The dependent variable P_{found_it} is the vector of the bad drug measures for prefecture i at quarter t, and two formats are tested: the number of bad drugs found by SFDA per million people in logarithm, and the dummy variable indicating at least one bad drug is found in prefecture i at quarter t. Ideally, the analysis should weight the number of bad drugs found by the drug market size in prefecture i at quarter t, but instead the population is used as the weight because of the absence of such data set. To allow for different forms of the correlation between the population and the local drug market size, I also add the population variable, $\ln pop_{it}$, as one of the explanatory variables on the right hand side.

W_{it} is the variable of interest, the Weibo use measure, and is defined as the logarithm of total number of Weibo posts including the Chinese word *hei* per 10,000 people from prefecture i at quarter t. Under the assumption that the introduction of Weibo is exogenous to the drug market, the parameter β is interpreted as the percentage change of the number of bad drugs found/the probability of having bad drugs found that is caused by 1 percentage point move on the measure of the Weibo use.

α_i is the vector of the prefecture fixed effects that accounts for the time invariable unobservable prefecture characteristics. λ_t is the vector of the quarter fixed effects that captures the time variable shocks. There are in total 16 time periods in the data, which is possibly long enough for the pretreatment data to establish a trend that can be extrapolated into the post-

[11] In logarithm.

[12] Because Weibo enters different prefectures in different quarter, the total number of event quarters is larger than the number of real quarters. Refers to table 1, after 2nd quarter of 2010 about half of all prefectures have Weibo entrance, which means fewer prefectures can experience 10 quarters before Weibo entrance(the total quarter is 16). Therefore, in the graph, I only show event timing from -9 to 8 that includes 9 time periods before and 9 time periods after Weibo enters.

treatment periods. Therefore, I control for the prefecture specific time trend in the regression, $\alpha_i * t$. ε_{it} is the error term.

The introduction of Sina Weibo is definitely not random, but it is arguably to be exogenous to the drug market. To support the argument and justify the identification as well as the specification, I check the determination of the Sina Weibo introduction. Form the check, it is expected to observe that the factors that mainly determine the Weibo use should not be correlated with the number of bad drugs found before Weibo enters. And then to test the robustness of the estimate, the factors that determine Weibo use are added into the regression.

I regress the ith quarter that Weibo enters and the average growth of the Weibo use measure since Sina Weibo became available on the baseline prefecture characteristics from 2008[13] to check which factors tend to predict the Weibo introduction. Results are reported in table 3. From column 1 and column 2, we can see that the GDP share from tertiary industry mainly predict the timing when the prefecture introduces Sina Weibo; and it together with the number of cellphone users, the education level (indicated by the education expenditure per capita) strongly predict the intensity of the Weibo use. However, the regression of the average number of bad drugs found before Weibo available on the baseline characteristics shows almost zero correlation between them (column 3, table 3) .It assures that the introduction of Sina Weibo is exogenous to the bad drugs issue in terms of observable prefecture characteristics. The estimate result also suggests a set of baseline controls that should be included in the regression for the robustness test. Hence, X_{it} includes the interaction terms between the three baseline characteristics and the year dummies. Besides that, to exclude the possible time variable confounders, X_{it} also includes the time varied value of the three variables, and factors that are often cited as the causes of the bad drug issue: GDP per capita, the number of hospital beds per 10,000 people, the share of agricultural sector labor force among the total, all in logarithm.

The Weibo use can influence the number of bad drugs found in either the positive way (by the screening effect) or the negative way (by the discipline effect). The negative sign is only observed when W is high. Since the Weibo use increases over time, it is important to check the dynamic effects of the Weibo use to reveal the whole picture of how the screening effect and the discipline effect work with different levels of the Weibo use. I apply the event study model to discuss the dynamic effects using the following regression:

$$P_{found\_it} = \eta \ln pop_{it} + \sum_{j=0}^{8} \beta_j W_{it} 1(\tau_{it} = j) + \alpha_i + \lambda_t + \alpha_i * t + \theta X_{it} + \varepsilon_{it} \quad (2)$$

Compared with the equation (1), one more index is added, τ_{it}. τ_{it} is the event quarter, and is defined so that $\tau_{it} = 0$ is the first quarter that W_{it} turns into positive, $\tau_{it} = 1$ refers to

[13]Control variables are statistics by year and Weibo became available since 4th quarter 2009, so 2008 prefecture characteristics are used as baseline.

1 quarter after Weibo enters the prefecture. The largest value for the possible τ_{it} is 8. The number of the coefficients of interest in equation (2) turns out to be 9, β_j, from the first period of Weibo enters $\tau_{it} = 0$ to the last possible period of the Weibo use $\tau_{it} = 8$.

Although the check of the determination of Weibo use on the observable prefecture characteristics lend some support to the exogeneity argument of the Weibo use to the drug market, there are still concerns related with unobservable characteristics. Section 7 will discuss the possible concerns in more detail and tests will be implemented to secure the argument that the effects estimated from equation (1) and (2) are causal.

Another important part of the empirical work in the paper is to check the channels via which Sina Weibo works. In order to check the relationship between the Weibo use and the administrator effort, $e'(w) > 0$ and $e''(w) < 0$, I rerun the equation (1) and (2) with the dependent variable replaced by the total number of the drugs checked by SFDA per million people in prefecture i quarter t , which is the proxy for the administrator effort. The results of the following equations will provide the empirical evidence that how the administrator responds to the Weibo use.

$$Ln\#\_check_{\mathrm{it}} = \eta \ln pop_{it} + \beta W_{it} + \alpha_i + \lambda_t + \alpha_i * t + \theta X_{it} + \varepsilon_{it} \quad (3)$$

$$Ln\#\_check_{\mathbf{it}} = \eta \ln pop_{it} + \sum_{j=0}^{8} \beta_j W_{it} 1(\tau_{it} = j) + \alpha_i + \lambda_t + \alpha_i * t + \theta X_{it} + \varepsilon_{it} \quad (4)$$

To check whether the Weibo use can help reducing the bad drugs though disciplining the drug producers, I re-construct the data by the location information of the producers and then re-estimate equation (1) with the corresponding variables measured by the producer location instead of the market location. If the discipline effect works through the producer, we expect to see the same sign of the coefficient estimate in the producer regression as the one in the market place regression (equation (1)).

In all regressions in the paper, standard errors are clustered at prefecture level.

6 Results

6.1 Main results

Table 4 reports the estimated βs and their clustered standard errors from equation (1). Column (1) and (2) report the estimate on the number of the bad drugs found, while column (3) and (4) report the estimate on the probability that the prefecture was found with the bad drugs, without and with prefecture level controls, X_{it}.

Table 4 column (1) suggests that 1 percentage point increase in the number of Weibo posts per 10,000 people decreases the number of the bad drugs found per million people by 0.107 percentage points. By column (3), 1 percentage point increase in the number of Weibo posts decreases the probability of having bad drugs in the prefecture by 0.324 percentage points. When prefecture level controls are added into the regressions, column (2) and column (4) tells the results as the robustness checks: the point estimates only decrease by 0.006 and 0.012 respectively. It suggests that the estimates of the effect of the Weibo use in column (1) and (3) are very robust. All estimates are statistically significant at either 1% or 5% level.

The magnitude of the effect estimate is considerably large. The mean of the total number of Weibo posts including *hei* per 10,000 people is 0.124 per quarter since the introduction of Weibo (Sep, 2009), and the appearance rate of the Weibo posts including *hei* is 0.0034. It means that there are around 36.5 Weibo posts per 10,000 persons per quarter, i.e. 0.00365 posts per person per quarter. According to the announcement, there are 50 million Weibo users in 2010[14] and 300 million out of total 1.37 billion population in early 2012[15], i.e.3.6% in 2010 and 22% of Chinese population use Sina Weibo. Let's take the number from the middle point of timing, 50 million users. According to the statistics, about 1/3 of users post at least one post per day. Reasonably let's assume the active Weibo user is also 1/3 of the total, i.e., 1.2% of all population. So, if everyone of them texts 1 more post per quarter, the average of the total Weibo posts will be increased by 328%[16], and then the number of the bad drugs found per million people in the prefecture will drop by 0.009[17]; and the possibility of having bad drugs found will be decreased by 5.7%[18]. If we measure the drug quality in the market by the number of the bad drugs found, the drug quality in the market is improved by almost 1/3[19]!

Table 5 reports the dynamic effects estimate from equation (2). From column (1) table 5, we can see that the estimate for $\beta_j s$ are all negative but only become steadily statistics significant until fourth quarter after Weibo enters. The similar pattern is also found in column (2) when prefecture level controls are added in but with larger standard errors. The estimates that are not statistically significant different from zero in the beginning of the Weibo introduction is due to the interaction between the big screening effect and the discipline effect. When the level of the Weibo use is low, a small marginal increase in the Weibo use can quickly reveal more bad drugs, which if not dominating, can completely counteract the discipline effect. When the screening effect is almost equal to the discipline effect, we then observe the "zero" effect of the Weibo use on the number of bad drugs found. When the Weibo use increases, the discipline effects beats the screening effect and then the number of the bad drugs found decreases in the Weibo use. Therefore, in the later periods, since the fourth quarter after Weibo enters, we observe that the Weibo use has the steady effect on reducing the number of

[14]http://technode.com/2010/11/17/50-millions-users-sina-microblogging-platform/

[15]http://en.wikipedia.org/wiki/Sina_Weibo

[16]0.012/0.00365=3.28

[17]The mean of the number of the bad drugs found per million people is 0.028, 0.028*0.10%*328=0.009

[18]The mean of the probability of having the bad drugs found is 0.054, 0.054*0.32%*328=5.7%

[19]0.009/0.028=0.32

the bad drugs found in the market.

Figure 5 plots the point estimate against the event timing of the Weibo introduction. By figure 5, we can see that from the first quarter Weibo enters, $\tau_{it} = 0$, to three quarters after Weibo enters $\tau_{it} = 3$, the 95% of confidence intervals are too wide to draw a certain conclusion. Since $\tau_{it} = 4$, the 95% confidence intervals shrink a lot to make the estimate showing statistically significant negative. Given the different significance pattern, I do two sets of F tests for coefficients β_0 to β_3, and for β_4 to β_8 to be jointly zero respectively. The F test results suggest that I cannot reject the coefficients β_0 to β_3 are jointly zero, but I can reject that the coefficients β_4 to β_8 are jointly zero.

The estimate of the dynamic effect is consistent with the model prediction: the discipline effect dominates the screening effects only when the Weibo use is high. That we do not observe the screening effect dominating might be because the Weibo use measure is the total number of the posts including the Chinese character with very low appearance rate, 0.0034. Hence, the very low level of the Weibo use cannot be indicated by the measure used in the paper.

6.2 Channels of the Effect of the Weibo use on the Drug Quality

Sina Weibo can reduce the number of the bad drugs provided in the market by pushing the administrator to work harder in regulating the drug market and by deterring the drug producer from producing more bad drugs. If the administrator is found to check more drugs in the prefectures where the Weibo use is higher, the direct result of the increased effort is that more bad drugs are found out, which is an evidence for the screening effect. If the number of the bad drugs found from the prefectures where they were produced is lower when the Weibo use is higher, it means the discipline effect dominating in these prefectures. This is an evidence for the discipline effect, and the discipline effect on the drug producer. The section will show the empirical discussion on the two channels.

6.2.1 The Administrator effort : $e'(w) \geq 0$ and $e''(w) < 0$?

The total number of the drugs checked per million people in the prefecture at the quarter is the index for the administrator - SFDA's effort. Replacing the left hand side variable with the logarithm of the total number of the drugs checked in equation (1) and (2), I re-estimate the equations and report the results in table 6.

Column (1) shows the overall effect of the Weibo use on the SFDA effort: where the Weibo use is higher, SFDA pays more effort on the drug checking but the estimate has no statistic significance. It can be due to the different reacting level in different time periods. As Sina Weibo increases over time, the reaction from SFDA is expected to be increasing in the beginning but the increase decreasing over time towards 0. When the average effect is estimated, the significance can be driven down by the large standard errors across times. So it is important to check the dynamic effects, and column (2) reports the result.

As we can see in column (2), SFDA starts to increase their effort one quarter after the introduction of Sina Weibo, but the increase significantly drops since the fifth quarter after the introduction till the last quarter in the sample. The timing interpretation is, SFDA may need some time to realize that they are subject to the accountability pressure that is caused by the Sina Weibo exposure, and then start reacting. The reaction in the beginning couples of event quarters is quite large: 1 percentage point increase in the number of the Weibo posts, more than 1 percentage point of the number of the drugs checked is increased. After several quarters of the extra effort implemented in regions with the higher Weibo use, the marginal return of the extra effort decreases considerably, so SFDA slows down the reaction. The statistic power shares the similar pattern with the point estimate, the statistic significance only appears before the fifth quarter after Sina Weibo enters. It suggests that when the Weibo use arrives at certain level, the marginal effect of the Weibo use on the SFDA's effort drops towards zero, $e'(w) \to 0$. Column (3) and (4) are the results with the prefecture level controls included in, and show the similar pattern as column (1) and (2) but with much larger standard errors.

Figure 6 imitates the SFDA's effort level across the introduction timing of Sina Weibo using the coefficient estimates in column (2). For each event quarter in x axis, the level indicated in y axis is the sum of the coefficient estimates up to the quarter. Hence, the comparative level of effort matters but the absolute level of y axis in figure 6 does not matter because we should add one constant number to all the imitative values if we want to estimate the absolute level of the effort. As we can see, the effort track is very similar with the one shown in figure 2 - the model prediction: it increases a lot in the first couples of quarters after Weibo enters but becomes more and more flat when the Weibo use is higher and higher. To further confirm the increase in the SFDA effort, I implement an F-test for the estimates of the effect of the Weibo use $\beta_j s$ from equation (2) and check whether they are jointly equal to zero. The F values are 3.7 and 2.8 for the regressions without and with the prefecture level controls (column (2) and (4)), while both reject the hypothesis that the coefficients $\beta_j s$ are jointly equal to zero at 1% significant level.

So far, the paper has shown that the number of the bad drugs found decreases in the Weibo use, and the SFDA effort increases in the Weibo use. Then by the model, it must be the case that the number of the bad drugs provided in the market has been decreasing in the Weibo use. And by corollary 1, the consumer welfare is better off because SFDA does react to the higher Weibo use.

6.2.2 Discipline effect on producers?

This subsection tests whether the discipline effect is associated with the drug producer. Although there is only one homogeneous drug provider in the model, in the real world there are two types of them: the producer and the distributor. As most of the bad drugs found are produced by the domestic drug manufacturers, it is expected that the drug producer is subject to the higher level of monitoring where the Weibo use is higher. Hence, we may observe the discipline effect on the drug producer.

To test the hypothesis, the producer information from each drugs checked in the *National drug quality announcement* is extracted and used. Whether the Weibo use in the prefectures where the drug producers are located in imposes some monitoring on the local drug producers is a complementary question to the one associated with the drug market location that I discussed before. Ideally, to answer the question, a data set including a large amount of representative producers' locations and their product quality information is needed. In lack of such data set, using the location information of the drug producers involved in the *National drug quality announcement* is the alternative. Collapsing the data by producer location, I get a set of data with similar structure as the one used in discussing the number of the bad drugs found in the market. The difference is now, the number of the bad drugs found is calculated by the prefectures where they were produced. If the drugs in the market are randomly drawn for the check by SFDA, the producers that produce the drugs will also be drawn randomly. It is the assumption that I use this data set to test the hypothesis of the discipline effect on the drug producer. (Appendix Figure B gives out a comparison between the distribution of the total product value of the pharmaceutical industry and the total number of drugs (produced in that location) checked by SFDA. It shows very similar patterns of the two, which assures the representativeness of the producer data I construct in this way.)

Using the data, I re-estimate the equation (1), but all variables are now measured in terms of the drug producers. Table 7 reports the result. Very strong effects are observed: on average, 1 percentage point increase in the number of the Weibo posts decreases about 0.14 percentage points of the number of the bad drugs found, and the estimate is statistically significant at 1% level. It is undeniable that there are also both the screening effect and the discipline effect existed when addressing the producer issue, but the negative net effect is driven by the dominating discipline effect and strongly proves the existence of the discipline effect on the producer.

In sum, I can conclude that Sina Weibo decreases the number of the bad drugs found in the market by pushing the administrator working harder and deterring the drug producers from producing the bad drugs.

7 Endogeneity Concern

A fundamental question the paper should answer is, whether the estimates from section 6 are causal effects? There are two big worries: one is the bad drug issue itself, and another is related with some other confounders. If the regions suffers less from the bad drug issue for some reason tend to have higher Weibo use since Sina Weibo became available, the estimate is then charllenged by reverse-causality problem. Another possibility is that there is some other confounders instead of Sina Weibo that affects the number of the bad drugs found, for example the general media pressure but not Sina Weibo per se. Or there are some unobservable confounders that predetermine the trend of the bad drug issue and the Weibo introduction simultaneously. This section suggests some tests to exclude these concerns.

7.1 Reverse-causality concern

Regions that suffer less from the bad drug issue tend to have healthier residents, who then pay more attention on other aspects of the life quality. For example, these people are more likely to have higher demand for the entertainment and the social life. As an instant communication media, Sina Weibo meets people's demand for fun and for the social life. In this case, the causality will run from the left to the right in equation (1).

To exclude the possibility, I regress the number of the Weibo posts since Weibo available and the ith quarter when Weibo enters on the average number of the bad drugs found before Weibo enters. If the reverse-causality concern is a problem, we should observe that the lower average number of the bad drugs found before Weibo enters predicts the higher Weibo use, and predicts an earlier quarter when Weibo will enter to the regions.

The results are reported in table 8. The point estimates in table 8 actually tell the story in another way around: regions with more bad drugs tend to have the higher level of the Weibo use in the future and tend to introduce Sina Weibo earlier. However, both estimates have no statistic power to support that there is some certain correlation between the average level of the bad drugs found before Weibo enters and the level of the Weibo use in the future. Based on this result, I claim that the lower level of the number of the bad drugs found has nothing to do with the Weibo introduction, and if there is any, it is in another way around, so the reverse-causality problem is not a concern in my study.

7.2 Concern of the Confounders : Placebo Tests

7.2.1 The General Media Pressure

There is possibility that the estimated effect of the Weibo use is not driven by the use of itself but just picks up the effect of the general mass media. In general, the mass media may have some effect on alleviating the bad drug problem. As Sina Weibo is one of the various media types, the measure of the Weibo use can just pick up the measure of the media pressure in the prefecture at the quarter. If it is not Sina Weibo, the measure of other type of media, newspaper for example, can also show the effect on the number of bad drugs found.

To exclude the possibility that the effect of Sina Weibo is due to the effect of other or general mass media, I implement the placebo test by fitting the following equation.

$$P_{found\_it\tau'} = \eta \ln pop_{it} + \beta' \ln\_\#\_\text{newspaper}_{iy} + \alpha_i + \lambda_t + \alpha_i * t + \theta X_{it} + \varepsilon_{it} \quad (5)$$

where $\ln\_\#\_\text{newspaper}_{iy}$ is the logarithm of the number of the newspapers per million people in prefecture i and year y . The data for this variable comes from Qin, Stromberg and Wu (2012). As the biggest and most influential traditional media in China, the number of the newspapers from the prefecture is a good measurement for the general media pressure. If the effect of the Weibo use just picks up the effect of the general media pressure, we should observe the estimate of β'in equation (5) is similar to the estimate of β in equation (1).

Column (1) and (2) in table 9 report the estimate results from equation (5), without and with the prefecture level of controls. From column (1) and (2), we can see the point estimates are very small positive numbers, 0.037 and 0.039, while the standard errors are too large to give the statistic power for the estimates. One cannot reject the zero effect of the newspaper on the number of the bad drugs found. Therefore, it confirms the analysis that the effect of the Weibo use estimated in section 6 is not driven by the general media pressure. The causal effect does run from the Weibo use to the number of the bad drugs found.

7.2.2 Other unobservable Counfounders

There might be other unobservable confounders determining the trend of the bad drug issue and the tendency to introduce Sina Weibo simultaneously. I use the staggered timing of Sina Weibo introduction in the identification. As long as the introduction timing and the variation of the Weibo use level is exogenous, the identification works. If the introduction is predetermined by some factor which at the same time determines the trend of the bad drug issue, the estimate will be questioned with the causal argument. For example, people in some regions care more about the regulating issue or social order, so that the number of the bad drugs in those regions has the declining trend. At the same time, since Weibo has the characteristic as a monitor, those regions tend to use Weibo earlier and more once it becomes available. In this case, the unobservable characteristics of the residents in that region determine the trend of the bad drug issue and the Weibo use even before Weibo enters.

I test whether the introduction of Sina Weibo is predetermined or not by inserting some pseudo points in the event timing. I move the Weibo use measure three periods forward, that is, a pseudo point when “Weibo enters” is 3 quarters before the real one. And then the number of the total Weibo posts including *hei* for the pseudo point is replaced by the number from the one in three quarters later. For the placebo test, I only include the data before Weibo enters. The regression for the test is as following:

$$P_{found\_it\tau'} = \eta \ln pop_{it} + \beta_1 W_{it\tau'} + \alpha_i + \lambda_t + \alpha_i * t + \theta X_{it} + \varepsilon_{it\tau'}, \tau < 0 \quad (6)$$

where τ' is the pseudo timing of the introduction of Weibo, $\tau' = 0$ when $\tau = -3$, and $W_{it\tau'} = W_{it\tau+3}$.

If the introduction and the intensity of Weibo use is predetermined, we should also observe some negative coefficient of $W_{it\tau'}$ as what we observe in section 6, β_1 should be statistically significant negative. Table 9 column (3) and (4) report the estimate. The point estimates for β_1 are really small, from -0.01 to 0.01, while the standard errors are huge. Therefore, it rejects that the pseudo number of the Weibo posts has some effect on the number of the bad drugs found. It excludes the possibility that there are some confounders predetermine the trend of the bad drug issue and the introduction of Sina Weibo, which lends a solid support for my identification used in the paper.

By excluding the two big groups of concern, I claim that the effects of the Weibo use on the number of the bad drugs found estimated in section 6 are causal.

8 Heterogeneous effects

Bate et. al (2011) suggest that the prevalence of the poor-quality drugs is associated with the low income level and literacy rate, so regions with higher GDP per capita and higher literacy rate may have lower level of the bad drugs. Sina Weibo has the low marginal delivery cost and once there is an access to internet or smartphone, there is an access to Weibo. Therefore, it is expected that for some ex ante disadvantageous groups, for example ones with the lower income and education level, as long as they can afford the entry cost, they may benefit more from the Weibo use.

A report from SFDA points out that rural areas in China suffer more from the bad drug issue[20]. In China, the rural area has on average the lower level of the consumption, so the low price and low quality drugs are especially popular there (Zhu, 2011). Additionally, most of the drugstores in the rural areas have small size that make the monitoring on them more difficult. All these factors can make the rural area as the target market of the bad drugs. Because there is no technical barrier that will differentiates the rural users of Weibo from the urban users, the introduction of Weibo can be more marginally helpful for rural areas.

Information is another important factor affecting the product quality in the market (Shapiro, 1982). The information cost increases in the distance between the producers and the market,

[20]http://www.safemedicinesindia.in/blog/2012/06/china-cracks-down-on-fake-drug-makers/

so it is reasonable to expect that a market far from its producers tend to have more bad drugs. When Sina Weibo comes in, more information can be widely spread regardless of the distance, so it is possible that Sina Weibo is more helpful for the markets that are far from their producers.

In sum, the bad drugs can be more popular in the regions with lower GDP per capita, the regions with lower education level, the markets far from the producers, and more rural regions. This part of analysis will check the heterogeneous effects that are associated with the four factors mentioned above. Without the education achievement data, I use the education expenditure per capita as a proxy for the education level. To measure how "rural" a region is, I use the share of the labor force from agriculture sector as an index. I split the whole sample into three equal partitions according to the baseline value (in 2008) for each of the four factors mentioned above, and then estimate equation (1) for each of the 12 data subsets.

The results for the heterogeneous effect estimates are summarized in table 10. From table 10, we can see that the Weibo use seems to have higher marginal effect on reducing the number of the bad drugs found in the group with middle level of GDP per capita: 1 percentage point increases in the Weibo posts, 0.46 percentage points of the bad drugs will be less likely to be found in the market, which is almost four times of the general effect estimate in section 6. However, the Weibo use does not seem to have any effect within the group with lowest GDP per capita. The reason might lie in the entry cost: the group with lowest GDP per capita may even have problem with access to internet or smart phone. The group with the lowest education expenditure has highest marginal effect of the Weibo use on reducing the number of the bad drugs found, and the estimate is actually marginally statistically significant, at around 12% level. The middle level of the education expenditure group benefit least, where both the economic magnitude and the statistic power are very low. The prefectures ranking secondly further from the producers seem to have higher marginal effect of the Weibo use. For the rural regions aspect, the prefectures with middle level of share of agriculture labor force seem to have highest marginal effect of the Weibo use, but the statistic power is too low to conclude.

What I can conclude from table 10 is, the regions with middle level of GDP per capita, regions with lowest education level, regions with middle level of the distance between the market and the producers tend to have higher marginal effect of Weibo use in terms of reducing the number of the bad drugs found in the market. The results suggest that the new format of media, Sina Weibo, compensates some ex ante disadvantaged groups to certain extent.

9 Conclusion

Understanding and squelching the bad drug issue in developing countries is a complex and arduous task in practice. It requires efforts and efficiency from many aspects. The study provides a possible new angle to process the issue: using the power of the new media, microblog. Actually, microblog is just one of the ways to spread out information and call on public attention through Internet. Therefore, taking advantage of Internet and exploring some similar media forms like microblog can obtain the similar effect.

In general, the effect of Sina weibo is the effect of a combination of information and public attention. Information enables the consumer and thus disciplines the product provider, so any way that may bring more information to the market can do good to promote the product quality. From the study, we observe the power of gathering the public attention, which imposes pressure on regulators and push them to work harder. As long as public opinions have the possibility to influent or threat the regime, even if it is an autocracy, the governor would not ignore them and are probably trained to be accountable to them. Sina Weibo does work in the China context is compelling evidence to it.

This study is a first attempt to discuss the possible role of media in solving the product quality problem and in creating government accountability under autocracy. Many detailed discussion might absent from the analysis, but those missing points definitely deserve more future research. For example, the information discussed in the paper has no differentiation on the true information or fake information, both of which exists in Sina Weibo and may have different effects. The paper does not analyze the effect of media on the drug retailer, neither the comparison of the effect on drug producers and retailors. Such comparison, however, might be crucial for understanding the bad drug issue since the bad drugs can be made during the production or in delivery process. All these works are meaningful to both academia progress and practical policy implication.

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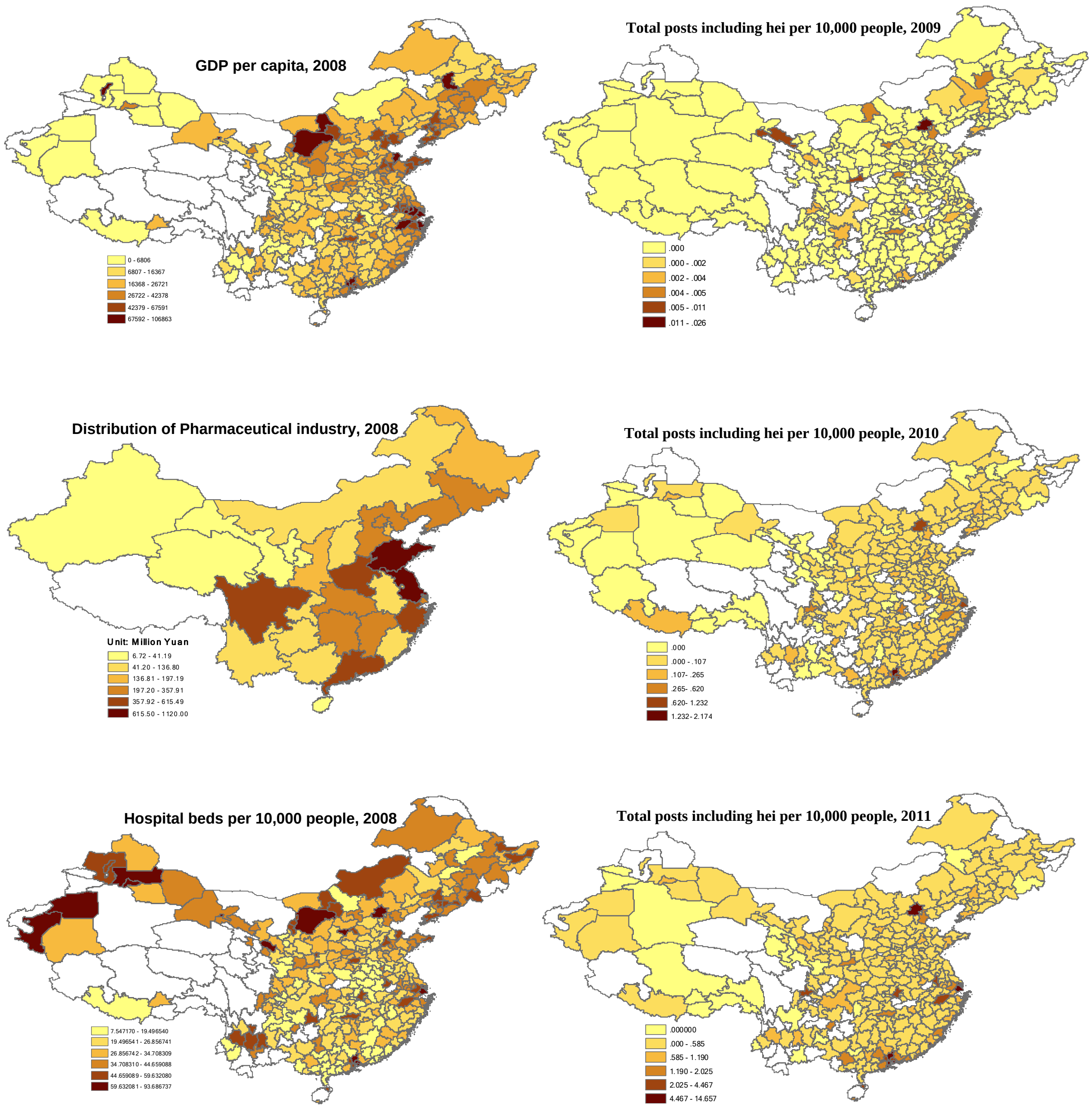
Figure 1 Weibo Use and Prefecture Characteristics



Notice: Data of the pharmaceutical industry production value comes from the Chinese High-tech Industry Statistics Yearbook 2008.

Figure 2 Model Prediction

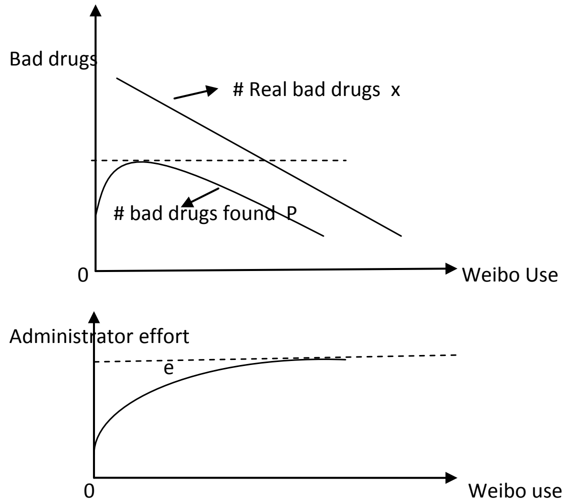


Figure 3 Distribution of Bad drugs Rate

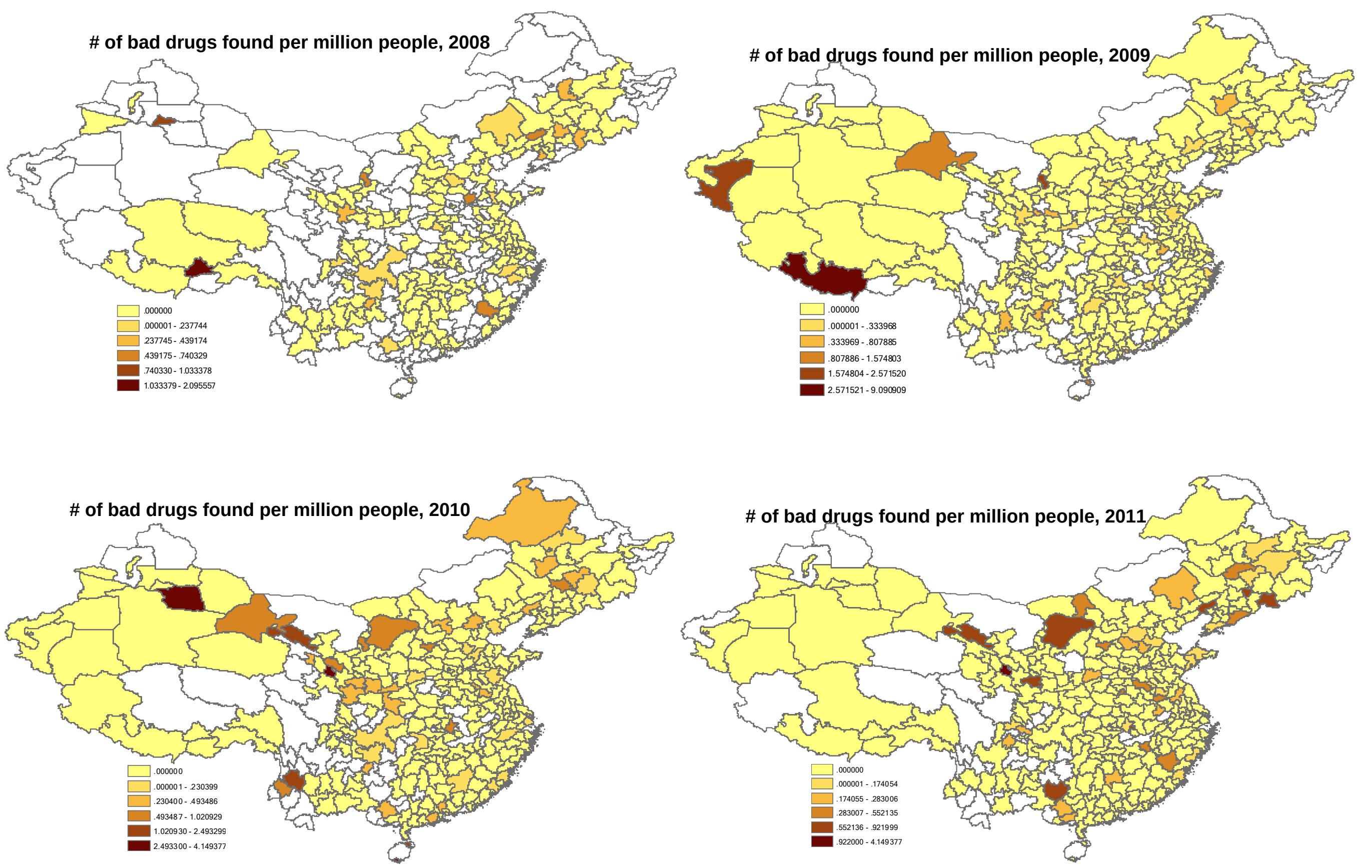


Figure 4: Identification: Difference-in-Difference

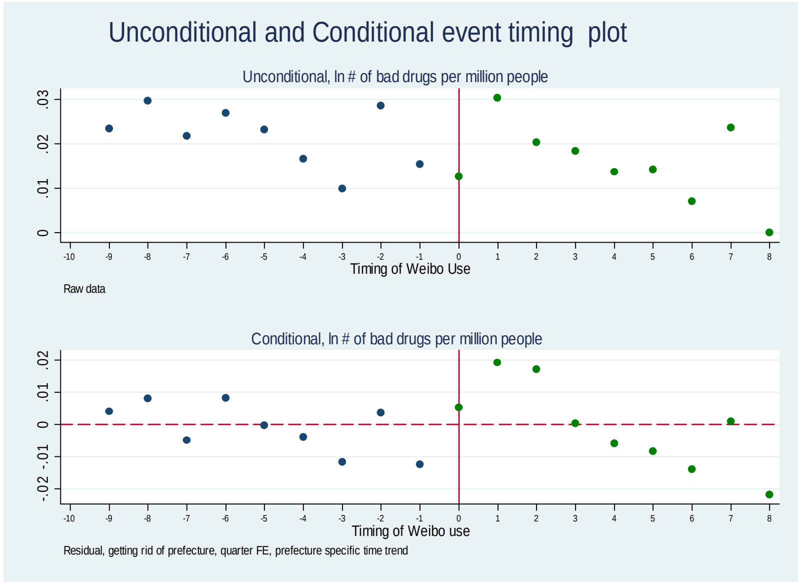


Figure 5

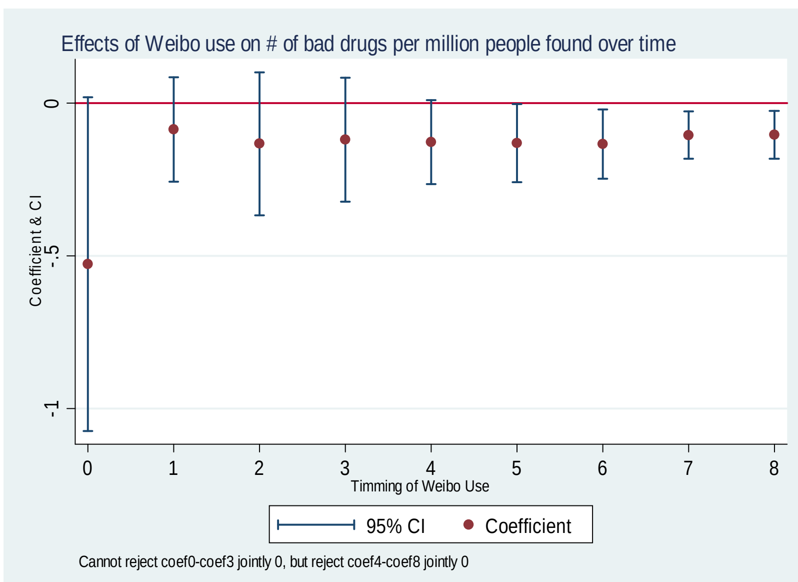


Figure 6

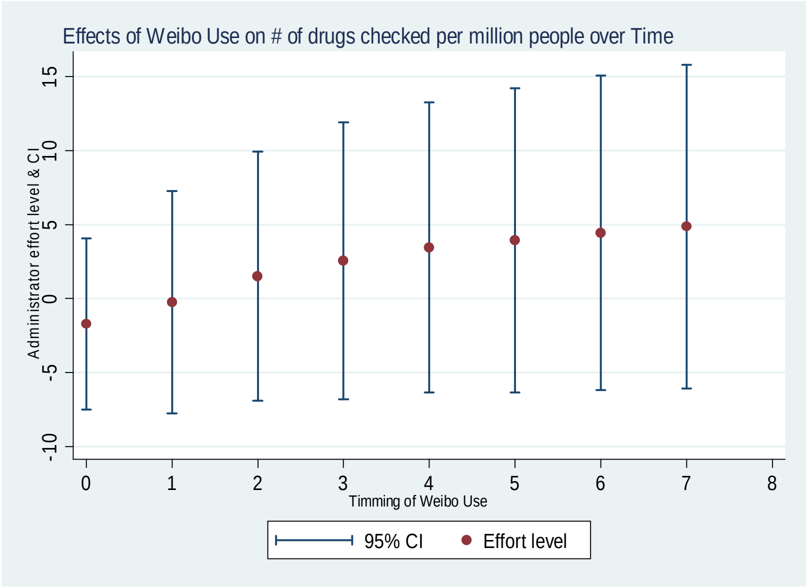


Table 1 Weibo use across time (#. of posts including hei, by prefecture)

Quarter	Obs	Mean	Std. Dev.	Min	Max
4th 2009	44	2.523	4.742	1	32
1st 2010	83	3.759	7.381	1	61
2nd 2010	154	6.006	15.549	1	120
3rd 2010	230	13.078	44.677	1	429
4th 2010	280	26.261	97.732	1	998
1st 2011	309	41.019	161.314	1	1762
2nd 2011	317	53.735	206.890	1	2344
3rd 2011	328	89.470	339.193	1	3556
4th 2011	334	96.638	351.660	1	3697

Table 2 Summary of Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
# total drugs checked	2977	13.938	21.364	1	216
# total drugs checked per million people	2977	4.620	9.849	0.088	227.273
# bad drugs	2977	0.065	0.294	0	4
# bad drugs per million people	2977	0.028	0.243	0	9.091
Ever had bad drugs found (prefecture i)	2977	0.432	0.495	0	1
Have bad dummy (prefecture I at period t)	2977	0.054	0.227	0	1
Population (Unit: 10,000)	2979	450	339	10.6	3303
Weibo_posts (per 10,000 people)	2977	0.062	0.282	0	4.864
GDP_pc (RMB)	2824	34124	23159	99	175125
Internet_user (per 10,000 people)	2825	1372	2557	0.604	36634.76
Cellphone_user (per 10,000 people)	2838	0.816	0.861	0.106	8.983
Hospital_beds (per 10,000 people)	2977	36.359	15.624	7.273	126.941
Education expenditure per capita (Yuan)	2838	793.97	599.57	140.56	5799.24
Distance (km)	2789	1001	800	0	7580
Period	3150	9.599	4.231	1	16

Table 3 Factors determine Weibo use

VARIABLES	i th quarter Weibo enters	Δ Ln_Weibo_posts	Avg. ln #bad before Weibo available
Ln_GDP_pc2008	-0.362	-0.001	0.004
	(0.545)	(0.006)	(0.014)
Ln_internet2008	0.191	-0.001	-0.009
	(0.379)	(0.004)	(0.007)
Ln_cellphone2008	-1.006	0.024***	0.008
	(0.639)	(0.007)	(0.018)
Ln_hospital_beds2008	0.605	-0.004	0.020
	(0.660)	(0.007)	(0.015)
Ln_eduexp2008	0.101	0.027***	-0.012
	(0.535)	(0.008)	(0.011)
Ln_distancetoBJ	0.064	-0.004	-0.008
	(0.409)	(0.005)	(0.005)
Ln_tertiary_gdpshare_2008	-2.747***	0.029***	0.027
	(0.596)	(0.006)	(0.017)
Province FE	YES	YES	YES
Observations	246	232	220
R-squared	0.330	0.801	0.165
N_prefecture	246	232	220

Robust standard errors in parentheses, clustered by prefecture. *** p<0.01, ** p<0.05, * p<0.1

Table 4 Impact of Weibo use on # bad drugs found in the market

VARIABLES	(1) Ln # bad	(2) Ln # bad	(3) Have bad	(4) Have bad
Ln_Weibo_posts	-0.107**	-0.101**	-0.324***	-0.312**
	(0.0416)	(0.0470)	(0.104)	(0.134)
Quarter FE	YES	YES	YES	YES
Prefecture FE	YES	YES	YES	YES
Prefecture specific trend	YES	YES	YES	YES
Controls		YES		YES
Observations	2,977	2,783	2,977	2,783
R-squared	0.232	0.251	0.219	0.225
N_prefecture	290	271	290	271

Robust standard errors in parentheses, clustered by prefecture. *** p<0.01, ** p<0.05, * p<0.1

Table 5 Dynamic effects of Weibo Use on # of Bad Drugs found

VARIABLES	(1) Ln # bad	(2) Ln # bad
Ln weibo posts _Ƭ=0	-0.527*	-0.482
	(0.273)	(0.355)
Ln weibo posts _Ƭ=1	-0.0853	0.0224
	(0.0857)	(0.157)
Ln weibo posts _Ƭ=2	-0.133	-0.228
	(0.117)	(0.186)
Ln weibo posts _Ƭ=3	-0.119	-0.143
	(0.102)	(0.151)
Ln weibo posts _Ƭ=4	-0.127*	-0.143
	(0.0690)	(0.0939)
Ln weibo posts _Ƭ=5	-0.131**	-0.136*
	(0.0638)	(0.0798)
Ln weibo posts _Ƭ=6	-0.134**	-0.134*
	(0.0568)	(0.0685)
Ln weibo posts _Ƭ=7	-0.104***	-0.101**
	(0.0386)	(0.0502)
Ln weibo posts _Ƭ=8	-0.104***	-0.104**
	(0.0392)	(0.0516)
Quarter FE	YES	YES
Prefecture FE	YES	YES
Prefecture specific trend	YES	YES
Controls	NO	YES
Observations	2,977	2,783
R-squared	0.233	0.253
N_prefectures	290	271

Robust standard errors in parentheses, clustered by prefecture. *** p<0.01, ** p<0.05, * p<0.1

Table 6 Impact of Weibo use on FDA effort of drug checking

VARIABLES	(1) Ln # check	(2) Ln # check	(3) Ln # check	(4) Ln # check
Ln_Weibo_posts	0.175		-0.0901	
	(0.315)		(0.404)	
Ln weibo posts _T=0		-1.728		-4.628
		(2.890)		(3.144)
Ln weibo posts _T=1		1.486		0.0874
		(1.202)		(1.320)
Ln weibo posts _T=2		1.749***		1.492*
		(0.629)		(0.865)
Ln weibo posts _T=3		1.041		0.894
		(0.644)		(0.856)
Ln weibo posts _T=4		0.903**		0.642
		(0.424)		(0.555)
Ln weibo posts _T=5		0.494		0.446
		(0.392)		(0.485)
Ln weibo posts _T=6		0.489		0.310
		(0.361)		(0.463)
Ln weibo posts _T=7		0.423		0.245
		(0.281)		(0.393)
Ln weibo posts _T=8		-0.291		-0.497
		(0.355)		(0.474)
Quarter FE	YES	YES	YES	YES
Prefecture FE	YES	YES	YES	YES
Prefecture specific trend	YES	YES	YES	YES
Controls	NO	NO	YES	YES
Observations	2,977	2,977	2,783	2,783
R-squared	0.794	0.796	0.785	0.788
N_prefectures	290	290	271	271
F-test for coef 0-8 jointly 0		3.685		2.789
Prob>F for coef 0-8 jointly 0		0.000218		0.00384

Robust standard errors in parentheses, clustered by prefecture. *** p<0.01, ** p<0.05, * p<0.1

Table 7 Impact of Weibo use on # bad drugs in production

VARIABLES	Ln # bad
Ln_Weibo_posts	-0.144***
	(0.0453)
Quarter FE	YES
Prefecture FE	YES
Prefecture specific trend	YES
Observations	1,750
N_prefecture	259
R-squared	0.291

Robust standard errors in parentheses, clustered by prefecture. *** p<0.01, ** p<0.05, * p<0.1

Table 8 Effect of # bad drugs found on future Weibo use/Weibo entrance

VARIABLES	Ln_Weibo_posts	*i* th quarter Weibo enters
Avg. Ln # bad before Weibo available	0.036	-1.030
	(0.031)	(1.204)
Observations	1,809	244
R-squared	0.606	0.215
N_prefecture	246	244
Province by Quarter FE	YES	
Province FE		YES

Note: Regressions in column (1) use data only since Weibo available, .i.e. 4th quarter, 2009
Robust standard errors in parentheses, clustered by prefecture. *** p<0.01, ** p<0.05, * p<0.1

Table 9 Placebo Test

	(1)	(2)	(3)	(4)
VARIABLES	Ln # bad	Ln # bad	Ln # bad	Ln # bad
Ln_#_newspaper_per million people	0.0373	0.0398		
	(0.0369)	(0.0397)		
Pseudo Ln_Weibo_posts			-0.0101	0.0144
			(0.272)	(0.381)
Observations	2,971	2,785	1,385	1,287
R-squared	0.230	0.250	0.306	0.443
N_prefectures	290	272	262	247
Quarter FE	YES	YES	YES	YES
Prefecture FE	YES	YES	YES	YES
Prefecture specific trend	YES	YES	YES	YES
Controls		YES		YES

Robust standard errors in parentheses, clustered by prefecture. *** p<0.01, ** p<0.05, * p<0.1

Table 10 Heterogeneous effects of Weibo use on # bad drugs found, by subsets of prefectures

	Lowest third	Second third	Highest third
Prefectures partitioned by:			
GDP per capita	0.210	-0.463*	-0.0728***
	(0.299)	(0.257)	(0.0258)
Distance between markets and producers	-0.0670*	-0.0804*	-0.348
	(0.0402)	(0.0415)	(0.269)
Education expenditure per capita	-0.189	0.0118	-0.0825*
	(0.122)	(0.0764)	(0.0423)
Share of agriculture labor force	-0.0935**	-0.280	-0.153
	(0.0372)	(0.239)	(0.245)

Robust standard errors in parentheses, clustered by prefecture. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Figure A: A piece of Sample of the Announcement Records

ID	Drug name	Labeled Producer	Production series No.	Format	Sample source	Judging rule	Testing institute	Test results	Unqualified iterm
序号	药品品名	标示生产厂家	批号	规格	检品来源	检验依据	检验机构	检验结果	不合格项目
1	盐酸二甲双胍肠溶片	贵州圣济堂制药有限公司	20080121	0.25g	广西壮族自治区南宁医药有限责任公司	国家食品药品监督管理局标准YBH25142006	内蒙古自治区食品药品检验所	合格	
2	盐酸二甲双胍肠溶片	贵州天安药业股份有限公司	20071239	0.25g	广西壮族自治区南宁医药有限责任公司	国家食品药品监督管理局标准YBH23102006	内蒙古自治区食品药品检验所	合格	

Figure B Compare distribution of pharmaceutical industry and number of drugs(by producer location) checked by SFDA

Corr.(production, # of drugs checked)=0.68

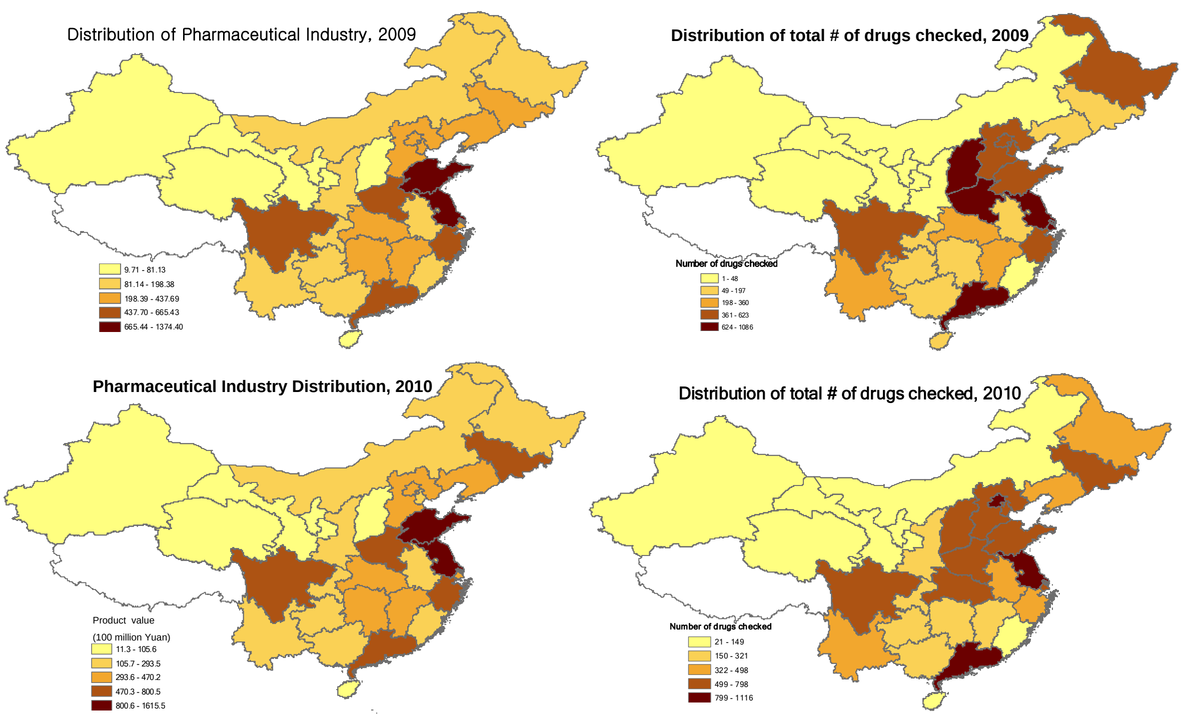


Table A Sampling Sources and Bad Drugs

	Full sample		Bad drugs sub-sample	
Sampling sources	Freq.	Percent	Freq.	Percent
clinics	1,922	4.75	8	4.57
disease control & prevention center,anti-epidemic stations etc. offices under the Health Department	252	0.62	1	0.57
drugstores	5,131	12.68	23	13.14
hospitals	11,298	27.92	42	24
intermediary drug companies	21,861	54.03	101	57.71
producers	3,262		28	
Total	43,726	100	203	100

Notice: Percent is calculated by excluding the number of producers from the sample.

Table B Categories of drugs

	Full sample		Bad drugs sub-sample	
categories of drugs	Freq.	Percent	Freq.	Percent
pharmaceutical excipient	16	0.04	0	0
respiratory system drugs	2,166	4.95	20	9.85
hormones and endocrine drugs	3,784	8.65	18	8.87
Analgesic, antipyretic, anti-inflammatory, anti-rheumatic, anti-gout drug	1,848	4.23	10	4.93
treatment of mental disorders drugs	293	0.67	3	1.48
anti-allergy drug	1,757	4.02	16	7.88
anti-microbial drugs	5,436	12.43	20	9.85
Antineoplastic drugs	60	0.14	1	0.49
the anesthetic	531	1.21	0	0
urinary system drugs	716	1.64	5	2.46
the immune system drugs	228	0.52	5	2.46
the nervous system drugs	2,381	5.44	4	1.97
Non-immunization other biotech-related drugs	42	0.1	3	1.48
vitamins, minerals, medicines	1,277	2.92	1	0.49
digestive system drugs	4,512	10.32	18	8.87
cardiovascular system drugs	4,540	10.38	9	4.43
blood system drugs	1,360	3.11	3	1.48
Immunization drugs	467	1.07	1	0.49
the diagnosis of drug	124	0.28	0	0
Traditional chinese medicine	11,551	26.41	61	30.05
specialty drugs	640	1.46	5	2.46
total	43,729	100	203	100