Decentralized Policy-Making and Market Distortions: Evidence from China's Drug Formulary Design*

Chenyuan Liu† Haiting Tian‡ Wanyu Yang§

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Abstract

Should public health insurance be administered at the national or sub-national level? This paper examines the issue in China's public health insurance drug formulary design. Before 2019, the central government allowed provinces to design their own public insurance drug lists. We find that provincial governments favor local firms, adding these firms' drugs disproportionately more in insurance coverage holding fixed local demand. We illustrate that a unified national formulary could eliminate such distortions but may induce welfare loss due to the central government's incomplete information and disregard for the heterogeneity of the local demand. *JEL Codes:* D72, I13, L65, O14, P21, R12.

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†Email: liuchy3@sem.tsinghua.edu.cn. Department of Economics, School of Economics and Management, Tsinghua University, Beijing, 100084, China.

‡HKU Business School, The University of Hong Kong.

§Center for Industrial and Business Organization and Institute for Advanced Economic Research, Dongbei University of Finance and Economics.

1 Introduction

In many countries, the central government establishes drug formularies for their public health insurance programs (Persaud et al., 2019). The drug formulary specifies which drugs are covered by the insurance program, providing an effective tool for the insurance program to negotiate lower drug prices, increase drug accessibility, and improve health outcomes (Duggan and Scott Morton, 2010). The design of drug formulary is thus particularly valuable for low-income households in developing countries. There is often a debate on whether the drug formulary should be administered nationally or sub-nationally. For example, the recent movement towards centralized health technology assessment calls for a unified coverage list to improve equity in access to healthcare (Tarricone et al., 2021).

Beyond the equity concern, there are often other aspects to consider. Theoretical literature in political economy has highlighted a trade-off in delivering public services by local rather than central governments: local governments often possess superior local information, but they are more likely to be influenced by interest groups and may create inter-jurisdictional spillovers (Bardhan and Mookherjee, 2000; Ogawa and Wildasin, 2009). The empirical literature has found evidence for both local governments' information advantage in managing state-owned enterprises (Huang et al., 2017) and the inefficiency in monitoring water pollution and carbon emissions due to externalities (He, Wang and Zhang, 2020; He, Pan and Xie, 2023).

This paper examines the trade-off between national and local policy-making in the context of the drug formulary design in China. China established a public health insurance program for urban employees in 1998 and specified a list of drugs covered by the insurance program, i.e., the drug formulary, in 2000. The formulary was subsequently revised in 2005, 2009, and 2017. The central government allowed drugs on the list to vary across provinces, enabling each province to take into consideration the disease prevalence variation and heterogeneous demand. However, in reality, anecdotal evidence suggests that local governments may exploit this authority to favor local producers and create market distortions.[1] In light of concerns for equity and local protectionism, the central government decided to unify the drug formulary at the national level in 2019.

Do provincial governments favor local firms when designing provincial drug formularies, and

[1] If a drug is included in the formulary, all products of the drug, generics or branded, local or non-local, are covered by the insurance program. However, provincial governments may still use the drug formulary to favor local firms by adding drugs produced mainly by local producers to insurance coverage. For example, a government report from Hunan province in 2016 explicitly stated the priority of local products in the design of the provincial drug formulary. See the following link (in Chinese): `https://www.hunan.gov.cn/xxgk/wjk/szbmwj/201607/20199245/files/ae74359e7bd94720953eceef36d52f0d.doc`.

if so, what are the social costs? We empirically examine these issues using various data sources. We hand-collect unique data on drug formularies in China's basic medical insurance program for 2005, 2009, and 2017, the second to fourth versions before the unifying policy reform in 2019. We supplement the baseline sample with yearly disease prevalence information, city-level quarterly drug sales information, and location, ownership type, tax contribution, and labor demand information on firms producing the drugs.

Using the data, we investigate whether the presence of local producers biases the provincial drug formulary design before 2019. Specifically, we compare the likelihood of being covered by the provincial drug formulary among drugs with and without a local producer. The correlation between the presence of local companies and the provincial insurance coverage for the corresponding drug may reflect other forces influencing both of them, such as the local demand for the drug. Another threat to identification is reverse causality, i.e., the potential leakage of information about a formulary change prompting local firms to enter the market ahead of the change. To address these concerns and establish causal links between the presence of local producers and the addition of a drug to the drug formulary, we employ two research designs. First, we restrict the comparison to drugs with similar indications and mechanisms, that is, drugs categorized under the same therapeutic classes. In a robustness check, we instead restrict the comparison among drugs treating the same disease. Second, we employ an instrumental variable design. While historical disease prevalence predicts the current product portfolio of local firms, some diseases have become less prevalent over time, and hence, historical demand no longer reflects current demand. We utilize the uncorrelated portion of historical disease prevalence with current disease prevalence as an instrument for the presence of local firms.

Overall, we find that the presence of local firms strongly predicts the drug being added to the provincial formulary, holding demand factors constant. Furthermore, the pattern is shown to be primarily driven by local state-owned enterprises (SOE) and joint ventures (JV) rather than other local private firms. These findings align with previous literature finding home bias in the automobile market in China (Barwick, Cao and Li, 2021). We also find that the effects are larger among local firms with higher tax contributions and more contributions to local employment.

A necessary condition for local protectionism in the drug formulary design is that local firms indeed benefit when their products are added to the formulary. We examine this condition by employing an event study and leveraging the 2017 drug formulary change. In support of the local favoritism hypothesis, we find that adding to the drug formulary significantly increases the total drug revenues, and local firms also grab a larger proportion of the increased revenue. In

contrast, we find no pre-trend in the local demand for drugs added to the provincial formulary, suggesting that formulary changes are not driven by provincial-specific demand shocks.

Ultimately, our concern lies with the welfare implications of allowing provincial governments to design drug formularies. We construct a conceptual model to illustrate the welfare implications of having a national uniform formulary (centralized policy-making) versus provincial formularies (decentralized policy-making). We consider a set of markets (provinces) with heterogeneous demand for drugs and varying preferences. Local governments have complete information on local demand, while part of the information is unobserved by the central government. Hence, the first best policy is achieved if each province designs its own formulary to maximize social surplus. However, local governments face private incentives when designing the formulary, which may not align with social welfare. For example, they may benefit from increased taxes and local employment if local firms' products are included in the provincial formulary. Hence, decentralized provincial formulary designs deviate from the first best.

Instead, if the central government designs the drug formulary, they could avoid the distorted incentives of provincial governments. However, they have less accurate information and may face further constraints of equalizing the drug formulary across provinces. We thus decompose the welfare difference between a centralized national formulary and a decentralized provincial formulary into three components: welfare loss due to incomplete information, welfare loss due to not accounting for heterogeneous preference, and welfare gain due to correcting the private incentives of provincial governments.

We quantify the trade-offs by estimating the decision function of provincial governments in the 2009 and 2017 formulary versions. We use disease prevalence variables to proxy the local welfare-relevant demand factors observed by both the central and provincial governments. The remaining welfare-relevant demand factors are assumed to be only observed by provincial governments. Besides, we use the presence of local firms to proxy the distortion factor in provincial government decision-making, while the rest of the distortion factor is unobserved to us. Therefore, the residual of the estimated decision function consists of the welfare-relevant (information advantage) and welfare-irrelevant (distortion) components. Since we could not empirically disentangle the two, we simulate two extreme scenarios: when the unobserved part is completely welfare-irrelevant and when it is completely welfare-relevant. We find that the welfare gain from the removal of local favoritism is much larger than the losses from not accounting for heterogeneous preference, while the welfare loss due to the incomplete information of the central government is sensitive to the assumption of the unobserved component. Overall, the centralized national formulary can greatly improve welfare relative to the provincial

decentralized formulary in the first scenario but not the second.

Our analysis contributes to the literature studying preferential policies favoring local firms (Young, 2000), especially in developing countries. The literature documents various channels through which this may occur, such as subsidies to local automobile manufacturers (Barwick, Cao and Li, 2021), implementation of environmental policies to favor the local automobile industry (Bai et al., 2021), discriminatory industrial policies (Bai, Tao and Tong, 2008), judicial capture (Liu et al., 2023), and biases in awarding government procurement contracts (Fang, Li and Wu, 2022). We illustrate a potentially under-explored mechanism through which local protectionism might arise: disproportionately covering drugs produced by local firms in drug formularies for insurance programs.

Our analysis of drug formulary design in China also connects to the healthcare literature on optimal drug formulary design. Most discussions pertain to the US health insurance markets. The previous literature examines the strategic formulary design of insurance companies in risk selection (Geruso, Layton and Prinz, 2019; Lavetti and Simon, 2018). Other works explore how the establishment of drug formulas in public health insurance programs may increase drug utilization and improve health, as seen in the US Medicare Part D (Duggan and Scott Morton, 2010) and Canada's compulsory health insurance (Wang et al., 2015). In the context of China, the previous literature documents that establishing the basic insurance program and drug formulary helps incentivize more innovation (Zhang and Nie, 2021). Other works find that the formulary design is affected by the political connection of the firm with government officials (Chen and Han, 2023). Our focus is on the optimal drug formulary design, concerning whether to vary it by province or to create a national list. Besides, our findings that insurance coverage enhances drug utilization are consistent with prior literature findings.

The outline of this paper is as follows. In Section 2, we provide the institutional details. In Section 3, we introduce our data and sample. In Section 4, we show our main empirical analysis. In Section 5, we delve into the welfare analysis. The final section concludes.

2 Institutional Background

China's pharmaceutical market is one of the largest in the world. In 2000–2018, drug expenditure increased from 221.12 billion CNY to 1914.89 billion CNY. Most pharmaceutical products consumed are off-patent products produced by local pharmaceutical firms, including domestic producers specializing in producing generic products and joint-venture firms producing and selling originator and on-patent drugs. The pharmaceutical market in China is characterized

by high segmentation, with over 5,000 domestic manufacturers (Kanavos, Mills and Zhang, 2019). Many of these manufacturers are small-scale, lack research and development capacity, face substantial entry barriers, and primarily cater to local markets.

One potential driver of China's significant and rapid growth in drug demand is the establishment of a basic health insurance program. In 2000, China introduced the "Basic Medical Insurance Drug Catalog," which listed the drugs covered by basic insurance programs and their respective coverage levels.[2] The formulary comprised two coverage tiers: Catalog A drugs received more extensive insurance coverage (full coverage), while Catalog B drugs entailed 10-20% consumer cost-sharing. For Catalog A drugs, the central government determined a unified national list for the whole country. However, for Catalog B drugs, due to the limited coverage capacity of the national drug formulary and significant differences in disease prevalence, medication habits, and economic development levels among regions, the central government only determined core National Catalog B drugs and allowed provincial governments to include extra drugs in the insurance coverage.[3] During the same period, the public health insurance program was administered mostly at the sub-national or sub-provincial level. Hence, allowing variations in Provincial Catalog B lists granted provincial governments significant autonomy in budget management through formulary decisions.

Since its establishment in 2000, the drug formulary has undergone revisions in 2005, 2009, and 2017, with some drugs added to or removed from the Catalog A, National Catalog B, and Provincial Catalog B lists. In 2019, the central government initiated a policy reform to gradually unify the provincial formularies into a single national formulary by 2022.[4] This policy shift was part of a series of efforts to transfer the administration of the social insurance system from the local to the central government. The primary rationale behind this policy shift is to address concerns about distorted incentives at the provincial level in drug formulary design: there is room for corruption due to lobbying by pharmaceutical firms. Provincial governments may also use the provincial formulary to favor local firms (Song, 2019). For example, a government report from Hunan province in 2016 explicitly stated that local products should be prioritized in their provincial drug formulary design.[5]

[2]In the drug formulary, the insurance coverage status varies at the active ingredient by dosage form (tablet, capsule, injections, etc) level. If a drug is included in the formulary, all products of that drug, branded and/or generics, are eligible for insurance coverage. However, due to market segmentation, not all products of the same drug were accessible in all provinces.

[3]According to the regulation, the number of drugs added at the provincial level should not exceed 15% of the National Catalog B drugs. In reality, however, we find this constraint often not binding.

[4]The 2019 national drug formulary still allows a few traditional Mongolian and Tibetan medicines to be covered in a separate drug formulary for the ethnicity minority groups.

[5]See the following link (in Chinese): `https://www.hunan.gov.cn/xxgk/wjk/szbmwj/201607/20199245/files/ae74359e7bd94720953eceef36d52f0d.doc`.

3 Data and Sample

We leverage the variation in provincial drug formularies across provinces before 2019 to empirically examine whether provincial formulary decision-making disproportionately benefits local firms, resulting in distortions. This section introduces our data sources and methods for constructing the sample.

3.1 Basic Medical Insurance Drug Catalog Data

We hand-collect data on the 2005, 2009, and 2017 versions of the Basic Medical Insurance Drug Catalog. Official resources, especially for earlier years, are limited. We collect the three versions of the Catalog A, National Catalog B, and Provincial Catalog B lists for more than 15 provinces from government websites, consulting reports, and white papers. Provinces with available data are listed in Appendix Table A1. In the drug formulary, the insurance coverage status varies at the active ingredient by dosage form (tablet, capsule, injections, or other) level. Certain dosage forms are grouped together in the formulary; for instance, normal-release tablets and capsules are combined in the category "regular oral dosage form". In the formulary data, the observations are at active ingredient by dosage form by province by formulary version level. For the rest of the paper, we use the term "drug" to denote the combination of active ingredient and dosage form. In addition, throughout the paper, we consider only the drug formulary design of Western medicines. Public insurance programs also cover traditional Chinese drugs. However, the classification and indications for these drugs are less clear, making the demand measurement tricky.

We establish a list of drugs that have ever been added to the 2005, 2009, or 2017 versions of Provincial Catalog B in some provinces. In total, there are 3,681 drugs. We then expand this list to construct a drug-province-version level sample, with each drug having 75 province-version observations where we have available information on Provincial Catalog B of that version in that province. Therefore, there are a total of 276,075 observations in the sample. We employ this sample as our baseline sample. In the baseline empirical analysis, we focus on 84,663 observations of the 2017 formulary version in the sample. For each observation, we generate a dummy indicating whether the corresponding drug is covered in the version of Provincial Catalog B in the province based on the drug formulary data.

We group the drugs in the baseline sample according to the Anatomical Therapeutic Chemical (ATC) classification system. The system classifies the active ingredients of drugs based on their anatomical, chemical, pharmacological, and therapeutic properties, as well as their

chemical substances. The ATC classification system comprises five hierarchical levels, with more disaggregated classifications at higher levels, and level 5 indicates individual drugs. Drugs within the same ATC 3 or 4 are considered closer substitutes for each other (Dubois and Lasio, 2018). We use this information to control for variations in disease prevalence and demand variations across drug groups.

Figure 1 plots the distribution of the number of drugs listed in Catalog A, National Catalog B, and Provincial Catalog B across provinces in the 2005, 2009, and 2017 versions. The blue and red lines indicate the number of drugs covered in Catalog A and National Catalog B, respectively, for which there is no variation across provinces. Over time, more drugs are included in these two formularies. The green boxes show the distribution of the number of drugs covered in Provincial Catalog B. The range is between 200 and 500, indicating that different provinces add different numbers of drugs to the provincial formulary. Figure 2 shows the variation in the compositions of the drugs listed in Provincial Catalog B across provinces in the 2017 version. To be specific, we calculate the fraction of drugs covered by Provincial Catalog B in each category of ATC 1 for each province and then plot the distribution across provinces for each category. As shown in the figure, there are some common patterns in all provinces: the most popular categories are A (alimentary tract and metabolism) and J (antiinfectives for systemic use). However, there are also large variations across provinces. For example, the fraction of drugs from the Provincial Catalog B in the J group varies between 8% and 27% across provinces.

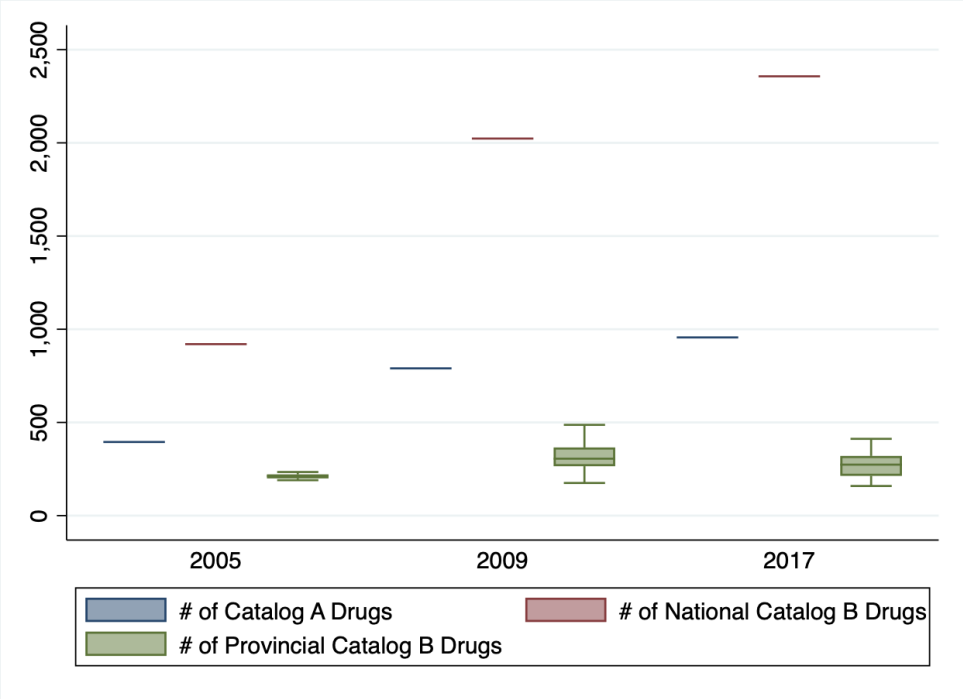
3.2 Disease Prevalence Data

To capture heterogeneous demand across provinces, we collect disease incidence ratio information at the province level for 31 diseases from the public health science database of the Chinese Center for Disease Control and Prevention (China CDC).[6] Figure 3 shows the difference in the disease incidence ratios per one million population between 2005, the first year we have the data, and 2008 or 2016, the years before the formulary change in 2009 or 2017 studied in this paper. As shown in the figure, incidences of most diseases, and hence the local demand, vary over time. In addition, the changes in disease incidences in 2005-2008 and 2005-2016 are positively correlated, suggesting that the disease incidences have a persistent time trend.

We manually match the diseases in the disease prevalence data with the corresponding treating drugs in the drug formulary data according to the drug indication information from

[6]The diseases are AIDS, anthrax, avian influenza, brucellosis, cholera, dengue fever, diphtheria, dysentery, epidemic cerebrospinal meningitis, epidemic encephalitis B, epidemic hemorrhagic fever, gonorrhea, leptospirosis, malaria, measles, neonatal tetanus, pertussis, plague, polio, pulmonary tuberculosis, rabies, scarlet fever, schistosomiasis, syphilis, typhoid and paratyphoid fever, and viral hepatitis A, B, C, D, E, and other.

Figure 1: Distribution of the Number of Drugs Listed in Each Formulary across Provinces



Notes: This figure plots the distribution of the number of drugs listed in Catalog A, National Catalog B, and Provincial Catalog B across provinces in the 2005, 2009, and 2017 formulary versions. The blue lines show the distribution for Catalog A, the red lines show the distribution for National Catalog B, and the green boxes show the distribution for Provincial Catalog B. Values outside 1.5 multiples of the inter-quartile range are not plotted.

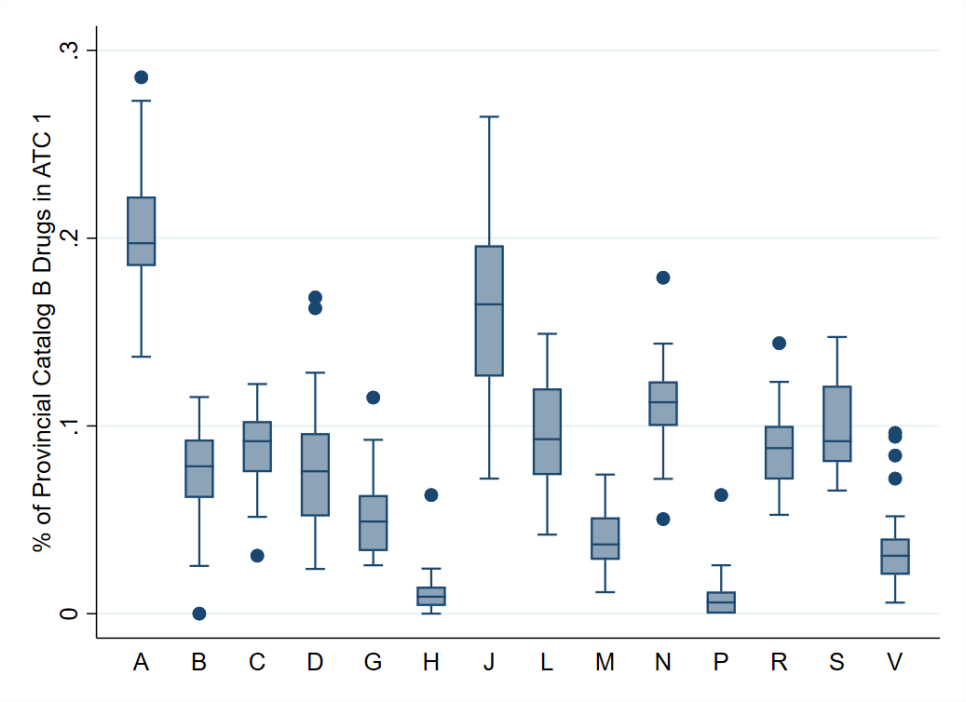
the drug registration data. For each drug in the formulary data, we generate indicators of whether the drug treats each disease in the disease prevalence data. For the rest of the diseases not included in the disease prevalence data, we label their corresponding drugs in the drug formulary data using drugs' ATC information following Costinot et al. (2019).

3.3 Firm Location, Ownership, and Portfolio Data

Our main analyses require information on pharmaceutical firms, including location, product portfolio, and ownership type. We collect such information from two major sources: the drug registration data from the National Medical Products Administration and China's Industrial and Commercial Registered Enterprises Database.

First, we establish a firm's product list using the drug registration data. This data include the initial registration date of each drug with the government. We use this information to identify whether the firm produced a specific drug at a specified time. The data categorize drugs based on dosage form using classification rules that differ from those in the formulary data. To ensure consistency in format classification across all datasets, we apply the classification rules

Figure 2: Distribution of the Number of Drugs Covered by Provincial Catalog B in Each ATC 1 Category across Provinces



Notes: This figure plots the distribution of the fraction of drugs covered by Provincial Catalog B in each category of ATC 1 across provinces in the 2017 formulary version.

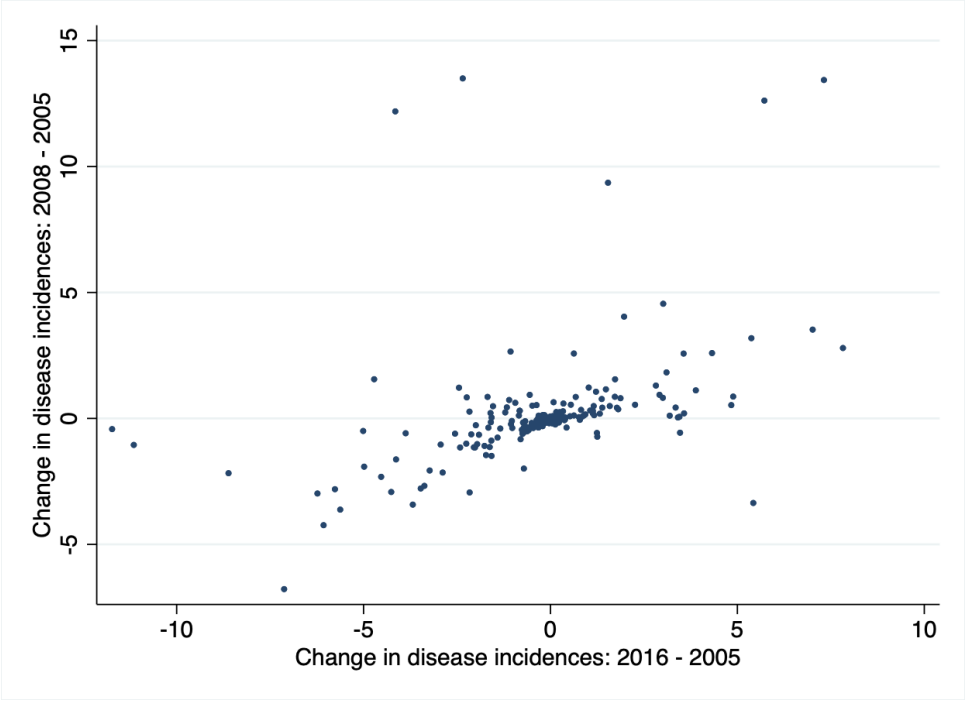
from the formulary data to reclassify the drug dosage form information in the registration data.

Second, we use the following steps to determine the location of a firm. We first collect information on firms' registration locations and main production sites in the raw data. If these are missing, we manually search the Internet to determine the locations. In almost all cases, the two locations coincide. Otherwise, we use the registration location.

Next, we match each drug in the baseline sample with its producing firms according to the firms' product lists. For each observation in the baseline sample, i.e., a drug by province by formulary version, we generate an indicator of the presence of as well as a variable of the number of local firms producing the corresponding drug in the province in the year prior to the formulary version.

Finally, we supplement the ownership information of the producing firms for each drug in the baseline sample using China's Industrial and Commercial Registered Enterprises Database. Firms are classified into four categories: state-owned enterprises (SOE), joint ventures (JV), domestic private firms, and foreign firms. The majority of firms are domestic firms.

Figure 3: Change in the Disease Incidence Ratios Over Time



Notes: This figure plots the change in the disease incidence ratios per one million population across time. Each observation represents a disease in a province. The x-axis shows the difference between 2016 and 2005, while the y-axis shows the difference between 2008 and 2005. The covered diseases are AIDS, anthrax, avian influenza, brucellosis, cholera, dengue fever, diphtheria, dysentery, epidemic cerebrospinal meningitis, epidemic encephalitis B, epidemic hemorrhagic fever, gonorrhea, leptospirosis, malaria, measles, neonatal tetanus, pertussis, plague, polio, pulmonary tuberculosis, rabies, scarlet fever, schistosomiasis, syphilis, typhoid and paratyphoid fever, and viral hepatitis A, B, C, D, E and others.

3.4 Drug Sales Data

We collect drug sales data from a consulting firm. The data record the quarterly sales revenue and quantity of Western drug products in 20 cities from 2013 to 2020.[7] The data are collected from more than 500 representative public hospitals and include detailed information on each product, including product name, production firm, main ingredients, route of administration, dosage form, strength, and package size.

In our analysis, we aggregate products based on active ingredients, dosage form, city, and quarter level, aligning with the structure of the drug formulary data. In the aggregation, we sum up the sales revenue of all product observations in a city in a quarter with the same active ingredient and dosage form but different package sizes, dosage weights, brands, etc., into a single observation. We also calculate, for each observation, the sales revenue share of the local firms,

[7]The included cities are Beijing, Changchun, Changsha, Chengdu, Chongqing, Fuzhou, Guangzhou, Hangzhou, Harbin, Jinan, Nanjing, Shanghai, Shenyang, Shenzhen, Shijiazhuang, Taiyuan, Tianjin, Wuhan, Xi'an, and Zhengzhou.

defined as firms located in the same province as the sales city. We then manually match the drug sales data with the baseline sample based on the information of the provinces where the cities are located to generate dummies indicating whether the drugs in sales data are covered by Catalog A, National Catalog B, some Provincial Catalog B, or none of them in each year and city.

3.5 Data on Firms' Tax Contributions and Labor Demand

We supplement our main analysis with pharmaceutical firms' tax contributions and labor demand to measure their bargaining power with local governments. For our main analysis, we collect tax information from the Chinese State Administration of Tax (SAT) survey data. The data samples representative Chinese enterprises with detailed information about their tax contributions. We also collect tax and labor demand information from the Annual Survey of Industrial Firms (ASIF) database.

For each observation in the baseline sample, we aim to calculate the tax contribution of local pharmaceutical firms from producing the corresponding drug in the province in the year prior to the formulary version. However, there is no information about a firm's tax contribution from its single product. Instead, we use the total contribution of a firm by selling all of its products produced, which may lead to some measurement error. Since the tax revenues collected from firms are ultimately shared between the central government and local governments, we conduct robustness checks by employing a firm's local tax contribution instead. In addition, we also turn to use a firm's income tax contribution collected from SAT or ASIF or a firm's tax over the total tax collected by the provincial government.

4 Evidence of Local Firm Distortion in Formulary Design

In this section, we explore whether provincial governments face distorted incentives when deciding the formulary. Specifically, we investigate whether the decision is driven by the presence of local drug producers holding fixed heterogeneous local demand for the drug.

4.1 Baseline Drug-Level Analysis

We conduct a cross-sectional comparison to test the existence of distortion in the provincial drug formulary. We use the baseline sample at the drug-province level in the 2017 formulary

version to estimate the following regression equation:

$$\mathbb{1}(ins)_{mp,2017} = \beta_0 + \beta_1 \mathbb{1}(local)_{mp,2016} + \theta_{ap} + \gamma_m + \varepsilon_{mp}, \tag{1}$$

where $\mathbb{1}(ins)_{mp,2017}$ is a dummy variable indicating whether drug m was included in province p's 2017 formulary version. $\mathbb{1}(local)_{mp,2016}$ is a dummy variable indicating the presence of any local firm producing m in 2016. γ_m denotes drug fixed effects. Standard errors are two-way clustered at the drug and province levels.

The biggest challenge to identification is the possible variation in disease prevalence across provinces just before the formulary change (i.e., in 2016), which can induce differential provincial demand for the corresponding treating drugs and, hence, lead to both the differential possibility of local firms producing the drugs and the differential likelihood of the drugs being added to the 2017 version of provincial formulary. We use two methods to address the issue. First, in the cross-sectional regression, we add ATC 4 by province fixed effects, θ_{ap}, to control for disease variation across regions. Thus, the comparison is within drug classes treating similar diseases in a province.

Second, we utilize an instrumental variable (IV) to isolate the variation in the presence of corresponding local firms that is uncorrelated with the demand induced by local disease prevalence just before the formulary change (i.e., in 2016). The idea is that disease prevalence may change over time. For example, a disease that was prevalent in the past may not be prevalent in the present due to improvements in income or changes in the demographics over time. We can separate the prevalence of the disease in 2005 (the first year we have the prevalence data) into two parts: the one that is still persistent in 2016 and should be incorporated into the formulary design in 2017 and the one that is no longer relevant in 2016 (namely, the residual). The residual part affects the demand in the past but no longer plays a role in the current demand. However, this part may affect firms' product portfolios not only in the past but also in the long run, thus correlated with the presence of local firms in the current time.

To be specific, we first estimate the following regression at the disease-province level:

$$s_{dp,2005} = \gamma_0 + \gamma_1 s_{dp,2016} + \eta_{dp}, \tag{2}$$

where $s_{dp,t}$ indicates the disease prevalence rate of disease d in province p in year t ($t = 2005$ or 2016). We estimate the residual term, $\hat{\eta}_{dp}$, which captures the part of the historical disease prevalence rate uncorrelated with the disease prevalence rate in the following years (thus

uncorrelated with current demand).

Appendix Table A2 provides supporting evidence for the above arguments. We find that $\hat{\eta}_{dp}$ is positively associated with local firms producing drugs treating the disease in the short run (i.e., 2005-2008, the subsequent years before a new formulary change). In addition, $\hat{\eta}_{dp}$ is also positively correlated with the presence of local firms producing drugs treating the disease in 2016, suggesting past demand has a persistent impact in the long run, even though the demand is no longer relevant in current times. However, we find that $\hat{\eta}_{dp}$ is not correlated with the presence of non-local firms in 2016, measured as whether there are any (or the number of) non-local firms selling the drug treating the disease in the province. The second fact suggests that non-local firms' current sales are not responsive to the residual demand in the past.[8]

For each drug, we then sum up the residual part of the prevalence rates of diseases the drug treats and employ it as an IV for the current presence of local firms producing the drug. To be specific, the IV is constructed as $z_{mp} = \sum_d \hat{\eta}_{dp} \mathbb{1}(Treat)_{md}$, where $\mathbb{1}(Treat)_{md}$ is a dummy indicating whether the drug m treats the disease d. z_{mp} is correlated with $\mathbb{1}(local)_{mp,t_0}$ as the local disease prevalence in 2005 is correlated with the presence of local firms producing the corresponding treating drugs in 2016. Furthermore, since the residual is orthogonal to the disease prevalence in 2016, the instrument is uncorrelated with the omitted local demand in 2016 in equation (1). In addition, the IV estimation also helps to address the potential reverse causality issue—firms' anticipation of changing formulary may drive local firms to enter the market before the formulary change.

Table 1 shows the baseline results. Column (1) estimates the equation (1) using OLS. Columns (2)-(4) show the reduced form, first stage, and IV results. The results show that drugs are more likely to be added to the provincial formulary if there is at least a local firm producing the drugs before the formulary change.

We examine the robustness of the results in Appendix Table A3, A4, and A5. We estimate equation (1) controlling for disease by province fixed effects, using the 2009 formulary version, employing the number of local firms producing the corresponding drug as the independent variable or adding ATC 3 by province fixed effects. All results are consistent with the baseline findings.

[8] We could not examine the correlation between $\hat{\eta}_{dp}$ and the presence of non-local firms in 2005-2008 because we only have sales data starting from 2013.

Table 1: Local Firm and Formulary Design

	OLS	Reduced Form	First Stage	IV
	(1)	(2)	(3)	(4)
	Covered by Insurance	Covered by Insurance	Presence of Local Firms	Covered by Insurance
Presence of Local Firms in 2016	0.031***			0.036***
	(0.003)			(0.004)
Instrument		0.005***	0.139***	
		(0.001)	(0.002)	
Observations	38,037	38,037	38,037	38,037
Drug FE	Y	Y	Y	Y
ATC4×Province FE	Y	Y	Y	Y
R^2	0.183	0.104	0.218	0.290
Adj. R^2	0.199	0.119	0.207	0.280
F-test			36.526	

Notes: This table presents baseline results using the baseline sample in the 2017 formulary version. Hence, each observation is a drug by province. "Presence of Local Firms in 2016" is a dummy variable indicating whether there was at least one local firm producing the corresponding drug in the year before the formulary change in 2017. "Instrument" is an instrumental variable constructed by predicting the part of the local prevalence of diseases that the corresponding drug treats in 2005 that cannot affect the local prevalence in 2016. Please see the text for the details. Standard errors are two-way clustered at the drug and province levels and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Event Studies with Sales Data

Given the evidence that drugs with local producers are more likely to be added to the provincial formulary, another question is whether local producing firms indeed benefit from the drug formulary design. To verify this, we employ a difference-in-difference specification to explore how adding drugs to the formulary changes drugs' total sales revenue and sales revenue share from local firms.

The analysis sample consists of drugs that were not covered by any formulary in 2013-2016 and were added to Provincial Catalog B in only some provinces in 2017. We compare drug-province observations that were not covered in 2013-2016 and were added to Provincial Catalog B in 2017 (treatment group) with the drug-province observations that were never covered in 2013-2019 (control group). Since sales information is only available at the city level, the comparison is essential across cities. In addition, due to cross-drug substitution, drugs that were not covered by any formulary in 2013-2019 may still be affected if there were other drugs in the same ATC 3 experiencing any type of insurance coverage change. Hence, we exclude such drugs from the control group.

We estimate the following event study regression:

$$Y_{mct} = \sum_{k=-16}^{16} \beta_k \mathbb{1}(t = \tau + k) \times \mathbb{1}(ins)_{mc} + \delta_{mc} + \lambda_t + \varepsilon_{mct}, \tag{3}$$

where Y_{mct} denotes the outcome variables of interest of drug m in city c in quarter t, including the logarithm of sales revenues and the revenue share from local firms. τ indicates the first quarter of 2017. $\mathbb{1}(t = \tau + k)$ indicates the calendar quarter that is k quarters before or after the first quarter of 2017. $\mathbb{1}(ins)_{mc}$ is a dummy variable indicating whether drug m is covered in the 2017 version of the Provincial Catalog B carried out in city c. We drop the interaction term of the period just before the formulary change in 2017 (i.e., $k = -1$) and set this period as the reference period. We add drug-by-city fixed effects δ_{mc} and year-quarter fixed effects λ_t to control for time-invariant local preferences for drug and national shocks. Standard errors are two-way clustered at the drug and city levels.

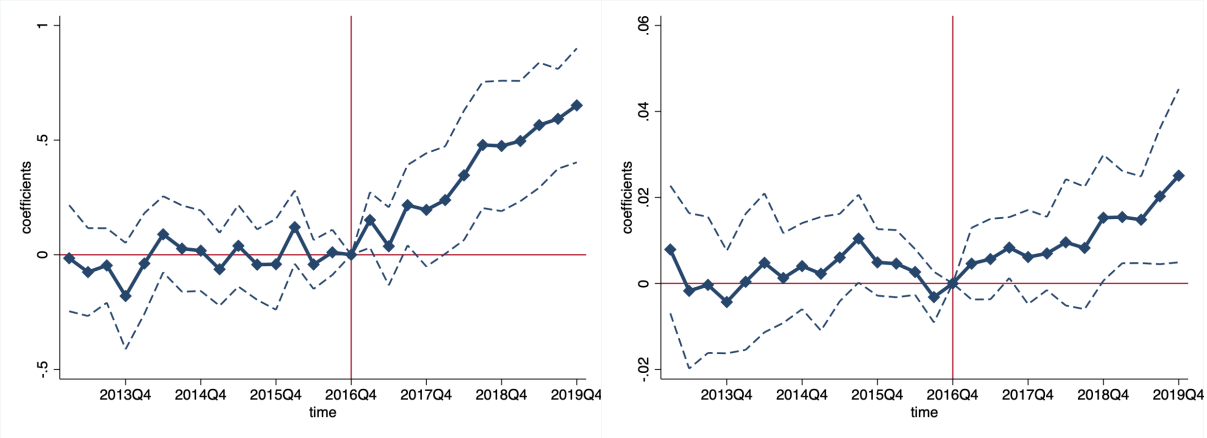
The coefficients of interest are β_ks ($k \geq 0$), showing the change in log revenue or local revenue shares due to the insurance coverage change. In addition, we are also interested in β_ks ($k < -1$), which indicate whether the treatment and control groups have different pre-trends in the outcome variable. If the formulary change is driven by local demand change over time, then there would be a pre-trend in the log revenues of the treatment group.

Figure 4 Panel A shows the results for log revenues. We find that the treatment group, drugs added to some Provincial Catalog B in 2017, experiences a significant relative increase in the log revenues in the corresponding city after the formulary change, compared with the control group. Three years after the formulary change, the relative increase in sales revenues is over 50%. This result confirms that insurance coverage increases drug demand. In addition to this, we also find that treatment and control groups have similar sales trends before 2017. There is no sudden change in demand right before the formulary change in the treatment city, indicating that local demand shocks do not drive the decision to change the formulary. In Panel B, we show how the increased demand is allocated across firms. We find that after being added to some Provincial Catalog B, the local firms have an increased market share. This finding further suggests that local firms indeed benefit more from the formulary change.

4.3 Mechanism

We further explore potential mechanisms of local preferences in the drug formulary design. We first investigate the heterogeneity effects across the local firms' ownership types. We classify

Figure 4: Event Study of the 2017 Provincial Formulary Change



(a) Panel A. Log Revenues

(b) Panel B. Local Firms' Revenue Share

Notes: This figure plots the effect of adding drugs to insurance coverage on drugs' total sales revenue (Panel A) and sales revenue share from local firms (Panel B). The analysis sample consists of drugs that were not covered by any formulary in 2013-2016 and were added to Provincial Catalog B in only some provinces in 2017. Hence, each observation is a drug by city by quarter. We compare drug-province observations that were not covered in 2013-2016 and were added to Provincial Catalog B in 2017 (treatment group) with the drug-province observations that were never covered in 2013-2019 (control group). Besides, we exclude from the control group drugs with some other drugs in the same ATC 3 experiencing any type of insurance coverage change, as these drugs may also be affected by the formulary change because of cross-drug substitution. Standard errors are two-way clustered at the drug and city levels. The dashed lines show the 95% confidence interval.

local firms into three ownership types—SOE, JV, and other private firms.[9] We construct three subsamples, each consisting of all the non-local drug-province observations, and local drug-province observations whose producers are of a specific ownership type in the 2017 formulary version. We then estimate equation (1) using each subsample. We instrument the presence of local firms producing a specific drug in a province with the constructed instrumental variable z_{mp} as in equation (2).

Table 2 shows the result. We find that the preference for local products in drug formulary design is strongest among SOE firms, smaller among JV firms, and smallest among other private firms. These results are consistent with previous literature on local protectionism, which also finds that local favoritism in the automobile industry in China is strongest among SOE and JV firms (Barwick, Cao and Li, 2021). The evidence lends further support to the local protectionism story: if the correlation of local insurance coverage and local firms' presence is both driven by local demand shocks, then it is hard to rationalize why firms of different ownership types respond to the demand shocks differently.

[9] A small fraction of firms are foreign firms, and we exclude them from the analysis because none of them are local firms.

Table 2: Drug Formulary Design and Local Firms' Ownership Type

	(1) SOE	(2) JV	(3) Private Firms
Presence of Local Firms in 2016	0.056***	0.022***	0.012**
	(0.008)	(0.009)	(0.006)
Observations	30,195	35,028	32,117
Drug FE	Y	Y	Y
ATC4×Province	Y	Y	Y
R^2	0.180	0.178	0.173
Adj. R^2	0.180	0.184	0.181
First Stage F-test	38.142	35.299	39.003

Notes: This table shows the heterogeneous results across the local firms' ownership types using the baseline sample in the 2017 formulary version. Hence, each observation is a drug by province. Column (1) ((2) or (3)) presents the 2SLS estimates in the subsample—each consisting of all the non-local drug-province observations, and local drug-province observations whose producers are only local SOE (JV or private firms). Please see the context for the details of the construction of the instrument variable. Standard errors are two-way clustered at the drug and province levels and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, we explore other firm characteristics that might affect local governments' decisions in designing the drug formulary. Local firms typically contribute to the local economy by generating tax revenues and creating job opportunities. We examine the heterogeneity of local protectionism across these characteristics. Similarly to the heterogeneity analysis across local firms' ownership, for each characteristic, we construct two subsamples, each consisting of non-local drug-province observations and local drug-province observations in the 2017 formulary version whose producers have a corresponding characteristic above or below the median across all observations. For the tax contribution amount or employment, we calculate it as the absolute amount of the tax contribution paid by or the total number of employees of all local firms producing the corresponding drug in the corresponding province. We then estimate equation (1) using each subsample and the IV method.

Table 3 shows the results. We find that local governments favor local firms with higher tax contributions more, as indicated by the difference in the coefficients between columns (1) and (2). In Appendix Table A6, we examine the robustness of the results by considering different tax measures and using different datasets. All results are consistent with the baseline ones. For employment, the differences are smaller and less significant.

Table 3: Formulary Design and Local Firms' Tax Contribution and Employment

	Tax Contribution Amount		Employment	
	above median	below median	above median	below median
	(1)	(2)	(3)	(4)
Presence of Local Firms in 2016	0.054***	0.018*	0.040***	0.028**
	(0.012)	(0.010)	(0.010)	(0.012)
Observations	29,026	29,026	29,026	29,026
Drug FE	Y	Y	Y	Y
ATC4×Province	Y	Y	Y	Y
R^2	0.178	0.195	0.172	0.170
Adj. R^2	0.179	0.201	0.177	0.176
First Stage F-test	44.185	27.760	47.789	20.130

Notes: This table uses the baseline sample in the 2017 formulary version to show the heterogeneous results across local firms' tax contribution amount and employment. Hence, each observation is a drug by province. Columns (1) and (2) show the heterogeneous results across local firms' tax contribution amount, which is calculated as the total tax paid by all local firms producing the corresponding drug in a province; columns (3) and (4) show the results across employment, which is calculated as the total number of employees of all local firms producing the corresponding drug in a province. Columns (1) and (3) ((2) and (4)) present the 2SLS estimates in the subsample consisting of non-local drug-province observations and local drug-province observations whose producers have a corresponding characteristic above (below) the median across all observations. Please see the context for the details of the construction of the instrument variable. Standard errors are two-way clustered at the drug and province levels and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Welfare Analysis

The above empirical evidence shows that the presence of local firms seems to bias the provincial drug formulary design in public health insurance programs in China. Such distortion may decrease social welfare because the decision to cover drugs is not purely based on the cost-efficiency of a drug but based on other factors. However, empirical literature in China and other countries also documents that local governments often have an information advantage over central governments and thus may better accommodate local demands. Ultimately, we care about the welfare consequences of replacing the decentralized provincial formulary with a centralized national uniform one. In this section, we first use a conceptual framework to highlight the trade-offs underlying the two types of formularies. We then map the stylized model to empirical counterparts and quantify the welfare implications of the 2019 policy change to unify the drug formulary nationally.

5.1 Conceptual Framework

Consider a nation with multiple markets (i.e., provinces). Provinces differ in disease prevalence, income levels, local preferences for health over other commodities, and other characteristics. Thus, residents in different provinces have heterogeneous preferences for covering each disease in the insurance program. The government makes decisions on whether to cover disease in medical insurance coverage, i.e., designing the drug formulary. There are two types of government agencies that could make such decisions: the central government and the provincial government. We assume that the latter has better information about the local conditional than the former.

Let p denote a province and d denote a disease. Covering a disease d for residents in province p creates the following net social surplus:

$$\delta_{dp} + \varepsilon_{dp}, \tag{4}$$

where δ_{dp} is the net social surplus observed by both the central and provincial governments, and ε_{dp} is an i.i.d. random component with mean zero. We assume that the central government knows the ex-ante distribution of ε_{dp}, while the ex-post realization of ε_{dp} is only observable by provincial governments. The net social value of covering the disease is the difference between the social benefits and the costs. For example, the benefits may include the reduced disease burden induced by insurance coverage. The costs include the treatment costs paid by the insurance and the potential overuse waste due to insurance coverage.

In addition, we assume that provincial governments may receive Δ_{dp}, a private value of adding the disease to the insurance coverage that is not relevant to social welfare. The private values may come from the tendency to favor local firms because of employment and tax concerns or bribery payments from certain firms.

Consider the following four types of drug formulary design scenarios:

First Best Formulary, c_0. Suppose there exists a social planner with complete information, observing δ_{dp} and also the realization of ε_{dp} for each disease and province. The social planner's goal is to maximize the total social surplus by designing the drug formulary:

$$\max_{c_{dp}} \sum_{d} \sum_{p} (\delta_{dp} + \varepsilon_{dp}) c_{dp}, \tag{5}$$

where c_{dp} is a dummy variable indicating whether to cover disease d for residents of the province p. In this stylized model, we assume that there is no substitutability or complementarity among the coverage for different diseases. We also assume that there are no spillover effects across provinces. Thus, the social surplus is the simple sum of all the surpluses of diseases across provinces. We normalize not covering a disease in the drug formulary as creating a surplus of zero.

Optimal decision-making requires the social planner to include a disease in the insurance coverage for a province only if the net social value of covering the disease in the province is positive, i.e., $\delta_{dp} + \varepsilon_{dp} > 0$. Let $c_{0,dp}$ denote the solution to (5). Then we have:

$$c_{0,dp} = \mathbb{1}(\delta_{dp} + \varepsilon_{dp} > 0). \tag{6}$$

Centralized Provincial Formulary, c_1. Now, suppose the central government designs the drug formulary. The central government could not observe the realization of ε_{dp}. As a result, the central government's goal is to maximize the ex-ante total surplus:

$$\max_{c_{dp}} \mathbb{E}\left[\sum_d \sum_p (\delta_{dp} + \varepsilon_{dp}) c_{dp}\right]. \tag{7}$$

The assumption that ε_{dp} is i.i.d with zero mean suggests that the central government includes disease d in province p's drug formulary only if $\delta_{dp} + E(\varepsilon_{dp}) = \delta_{dp} > 0$. Thus, the solution to (7) is:

$$c_{1,dp} = \mathbb{1}(\delta_{dp} > 0). \tag{8}$$

Centralized National Formulary, c_2. Sometimes, the central government faces extra constraints. In particular, due to equity concerns or political reasons, the central government may not be able to vary the drug formulary by province. Suppose that the central government designs a single formulary for all provinces. It considers the ex-ante aggregate social benefits of covering diseases across all provinces:

$$\max_{c_d} \mathbb{E}\left[\sum_d \left(\sum_p (\delta_{dp} + \varepsilon_{dp})\right) c_d\right]. \tag{9}$$

Let $c_{2,d}$ denote the solution in this scenario. Given that ε_{dp} is i.i.d with zero mean, we have:

$$c_{2,d} = \mathbb{1}(\sum_p \delta_{dp} > 0). \tag{10}$$

Decentralized Provincial Formulary, c_3. Finally, suppose provincial governments design the drug formulary. Provincial governments would consider both the social surplus and the private values when deciding whether to cover a disease. The objective function is:

$$\max_{c_{dp}} \sum_d \sum_p (\delta_{dp} + \varepsilon_{dp} + \Delta_{dp}) c_{dp}. \tag{11}$$

Let $c_{3,dp}$ denote the solution to (11). Then we have:

$$c_{3,dp} = \mathbb{1}(\delta_{dp} + \varepsilon_{dp} + \Delta_{dp} > 0). \tag{12}$$

To compare the welfare of each scenario, we use the ex-ante total social surplus, denoted by W_k, with $k = 0, 1, 2, 3$. The ex-ante welfare under each scheme is:

$$W_k = \mathbb{E}\left[\sum_p \sum_d c_{k,dp}(\delta_{dp} + \varepsilon_{dp})\right], \forall k = 0, 1, 2, 3. \tag{13}$$

We can mechanically decompose the difference in welfare between having a national uniform formulary as in the case after 2019 ($\boldsymbol{c_2}$) versus a decentralized provincial formulary ($\boldsymbol{c_3}$) in the following terms:

$$W_2 - W_3 = \underbrace{W_2 - W_1}_{\substack{\text{loss due to} \\ \text{neglect of} \\ \text{heterogeneous} \\ \text{preference}}} + \underbrace{W_1 - W_0}_{\substack{\text{loss due to} \\ \text{incomplete} \\ \text{information}}} + \underbrace{W_0 - W_3}_{\substack{\text{benefits of} \\ \text{removing} \\ \text{distortion}}}.$$

The first best drug formulary $\boldsymbol{c_0}$ yields the highest welfare because a disease is covered in this formulary only when the social welfare is larger than zero. All other drug formularies deviate from the first best and create some welfare loss. We label the difference between the welfare of each drug formularies in the following ways. First, the difference between W_0 and W_1 denotes the loss in welfare due to incomplete information: the central government has less accurate information on ε_{dp} when designing the drug formulary and therefore achieves lower social surplus than the social planner. Second, the difference between W_2 and W_1 denotes the loss in welfare due to neglect of the preference heterogeneity (i.e., the social surplus heterogeneity) across provinces when unifying the formulary among provinces. Forcing all provinces to have the same drug formulary imposes extra constraints on the design and further reduces the social surplus. Finally, the difference between W_3 and W_0 indicates the difference in welfare due to the private incentives of provincial governments that tend to favor local firms.

The model highlights the following trade-off between centralized and decentralized decision-

making: centralized decision-making removes the distortion from local governments' private incentives at the cost of welfare loss due to incomplete information. If the central government is further constrained to only having a national uniform drug formulary for all provinces, then the benefits of removing local governments' private incentive distortion are weighted against both the losses due to incomplete information and the losses due to not accounting for heterogeneous preferences.

The welfare comparison of a decentralized provincial formulary and a centralized national formulary depends on the relative size of the information shock, ε_{dp}, the private incentives, Δ_{dp}, and the extent of the heterogeneous preference. For example, if the unobserved welfare-relevant noise $\varepsilon_{dp} = 0$, then $W_1 - W_0 = 0$: there is no incomplete information, and therefore, centralized decision-making does not result in welfare loss. If $\Delta = 0$, then $W_3 = W_0$, and thus the provincial decentralized formulary achieves the first best. Therefore, we empirically evaluate the relative size of these three forces in the next subsection.

5.2 Empirical Model

We employ the baseline sample in 2009 and 2017 formulary versions to calibrate the model to illustrate the potential welfare implications of the four types of policies discussed in the above subsection. We make the following parametric assumptions for the model components. First, we assume that the observed net social value of covering the disease d in province p takes the following form:

$$\delta_{dp} = \alpha_{1,d} n_{dp} + \alpha_{2,d} n_{dp}^2 + \theta_p,$$

where n_{dp} is the disease prevalence, measured as the number of individuals suffering disease d in province p in the year before the formulary change. We assume that the net social benefit of covering the disease is a quadratic function of the number of individuals affected. The parametric form takes into account the potential non-linearity in the benefits of covering the disease with regard to the infected population size. We allow the coefficients of n_{dp} and n_{dp}^2 to be disease-specific, capturing the varying severance of the disease and different economic values of covering diseases. In addition, we control for province fixed effects θ_p in the equation to capture heterogeneous preference for covering diseases in different provinces, for example, because of different economic development levels. Note that the central government's information should be at least as large as that observed by us. Thus, we estimate an upper bound of the welfare loss due to incomplete information.

Motivated by the empirical results in section 4, we model the private value term as follows:

$$\Delta_{dp} = \mathbb{1}(local_{dp}) + \omega_{dp},$$

where $\mathbb{1}(local_{dp})$ is a dummy variable indicating whether there exists any local firm in the year before the formulary change producing the drugs treating disease d in province p, and ω_{dp} is an i.i.d. random component with mean zero, unobserved by us but observed by the provincial government. Note that the favoritism towards local firms for economic reasons leads to distortion from the perspective of the whole society. Consider the following example: there are two drugs treating the same disease but being produced by different firms in different provinces. Suppose that drug A is a more socially efficient way to treat the disease (for example, it has a lower cost or better treatment outcome.) From the national perspective, all residents in both provinces should take drug A. However, only one province has incentives to add drug A to the drug formulary, as the other province with a local firm producing drug B may suffer some losses in employment, tax revenue, or bribery payments if it adds drug A instead of drug B to its drug formulary.

We recognize that provincial governments' private incentives may take different forms. For example, in addition to the incentives to favor local firms, they may be lobbied by other firms, especially those with strong political connections. Unfortunately, those types of private incentives are harder to capture with our data. Our estimates based on the presence of local firms should be viewed as a lower bound of the size of the private incentives.

Finally, we introduce an unobserved random component, $e_{dp} = \varepsilon_{dp} + \omega_{dp}$, which is the sum of the unobserved welfare-relevant component and the unobserved private value component. We assume e_{dp} is iid with a standard normal distribution. We normalize the variance of e_{dp} as one since, for any other variance, we could always divide all coefficients by the standard deviation of e_{dp} while yielding the same coverage decision results. Thus, all coefficients in our model are essentially identified as the ratio relative to the standard deviation of e_{dp}. We cannot empirically disentangle the unobserved welfare-relevant component and the unobserved private value component. Thus, we consider two extreme scenarios: $e_{dp} = \omega_{dp}$ or $e_{dp} = \varepsilon_{dp}$. The former assumes that there is no information advantage for provincial governments, i.e. $W_1 = W_0$. Thus, the welfare difference between the centralized national formulary and the provincial decentralized formulary is a trade-off between heterogeneous preference and local distortion. The latter assumes that all the unobserved (to us) factors affecting provincial governments' decision-making are welfare-relevant. The reality should lie somewhere in between the two

cases.

We estimate the following probit model of the decisions of provincial governments using the maximum likelihood estimation:

$$c_{2,dp} = \mathbb{1}(\theta_p + \alpha_{1,d} n_{dp} + \alpha_{2,d} n_{dp}^2 + \beta \mathbb{1}(local_{dp}) + e_{dp} > 0). \tag{14}$$

Specifically, we estimate the equation by pooling the 2009 and 2017 versions of the provincial drug formulary. For the 2009 (2017) formulary version, We calculate n_{dp} using the disease prevalence data in the year 2008 (2016). The one-year lag ensures the decision-making is based on the most recent disease prevalence conditions. The 2005 formulary version is dropped because we only have information on disease prevalence after 2005.

5.3 Results

Table 4 shows the estimates. We convert the coefficient of $\mathbb{1}(local_{dp})$ into the marginal probabilities of covering the disease in the provincial formulary. Column (1) shows the results using the probit model. The estimate shows that having a local firm in the year before the formulary change increases the probability of being covered by the provincial formulary by over 40%, keeping fixed the prevalence of the disease and controlling for provincial fixed effects. Columns (2) and (3) show the robustness results using logit and linear probability models, which are consistent with the baseline result in column (1).

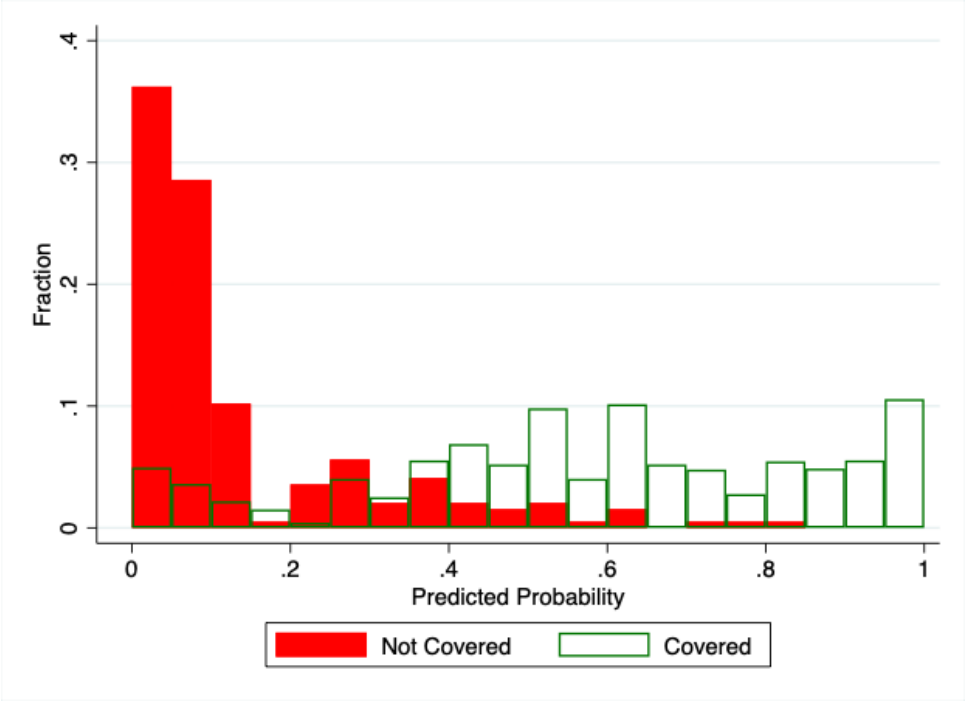
Table 4: Marginal Probabilities of Presence of Local Firms

	(1) probit	(2) logit	(3) linear probability model
Presence of Local Firms, $\hat{\beta}$	0.431***	0.437***	0.450***
	(0.036)	(0.036)	(0.039)
Number of Observations	1,388	1,388	1,388

Notes: This table uses the baseline sample in 2009 and 2017 formulary versions to estimate equation (14). Hence, each observation is a disease by province by version. The dependent variable is whether the 2009 or 2017 version of the drug formulary covers the disease. The incidence rate is measured as the number of incidences per 100 million population in the year before the formulary change. The first column uses the probit model, the second uses the logit model, and the last uses the linear probability model. The estimates are the marginal probabilities of the dummy variable indicating the presence of local firms in the year before the formulary change producing drugs treating the corresponding disease, with province-level clustered standard errors in parenthesis. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We then use the estimated result with the baseline probit model to quantify the welfare effects of replacing the provincial formulary with a national uniform formulary. Our calculation goes as follows: first, we predict $\hat{\delta}_{dp} + \hat{\Delta}_{dp}$ and hence the predicted probability that a disease would be covered by provincial insurance using the baseline model, the probit specification. Figure 5 plots the distribution of predicted probabilities for diseases in the provinces where the diseases were covered by provincial insurance (white bars with green boundary) and for diseases in the provinces where the diseases were not covered (red bars) in the baseline model. The figure shows that the diseases in the provinces where the diseases were covered by the provincial insurance have higher predicted probabilities, indicating a good model fit. We then use the predicted $\hat{\delta}_{dp}$ and $\hat{\Delta}_{dp}$ to calculate the ex-ante social welfare under each scenario. We collect the calculation details in Appendix B.

Figure 5: Model Fit



Notes: This figure plots the distribution of predicted probabilities for diseases in the provinces where the diseases were covered by provincial insurance (white bars with green boundary) and for diseases in the provinces where the diseases were not covered (red bars) in the baseline model. The predicted probability that a disease would be covered by provincial insurance is estimated using the probit model in equation (14).

Table 5 shows the results. Panel A shows the welfare estimates for each type of formulary. Panel B decomposes the welfare change due to the 2019 uniform drug formulary policy into three channels. Note that we do not have monetary values in the estimation equation and hence cannot convert the value to monetary terms. Thus, estimates can only be interpreted as relative welfare values between different types of policies. We set W_0, the welfare estimate of the first best

Table 5: Welfare Estimates

Panel A. Welfare

	W_0	W_1	W_2	W_3
$\varepsilon = 0$	228.78	228.78	140.93	-477.87
	(475.58)	(475.58)	(460.86)	(486.19)
$\omega = 0$	2655.35	228.78	140.93	837.97
	(469.78)	(475.58)	(460.86)	(457.91)

Panel B. Decomposition of $W_2 - W_3$

	Total $W_2 - W_3$	Loss: Heterogeneous Preference $W_2 - W_1$	Loss: Incomplete Information $W_1 - W_0$	Benefits: No Local Distortion $W_0 - W_3$
$\varepsilon = 0$	618.80	-87.85	0.00	706.64
	(97.64)	(50.40)	/	(82.64)
$\omega = 0$	-697.04	-87.85	-2426.57	1817.38
	(106.04)	(50.40)	(179.21)	(224.08)

Notes: This table presents the welfare estimates for four types of formularies based on the estimates of equation (14) in column (1) in Table 4 —the first best formulary designed by a social planner with complete information on the net social surplus in all provinces, the provincial formulary designed by the central government with incomplete information, the national uniform formulary designed by the central government, and the provincial formulary designed by provincial governments. Standard errors in parentheses are obtained as the empirical standard deviation across 1000 independent random draws of the parameters using the estimated variance-covariance matrix.

formulary, as a benchmark. In both panels, the first row shows the case where the unobserved factors in the provincial governments' decision function are welfare irrelevant. By construction, there is no loss due to incomplete information in a centralized national drug formulary. We find that, in this case, the local distortion of provincial governments greatly reduces the social surplus by over 700. In contrast, having a national uniform formulary reduces the surplus only by less than 90. The local private incentive distortion is significantly more important than the heterogeneous preference channel. Thus, unifying the drug formulary nationally greatly improves social welfare.

In both panels' second row, we illustrate the case when the unobserved factors are all welfare-relevant. In this case, the information advantage of provincial governments dominates: the losses due to incomplete information of the centralized government is about 2400, while the savings from removing the local distortion are only 1800. Combined with a 90 loss from not accounting for heterogeneous preference, the centralized national uniform formulary achieves 700 less social surplus than decentralized provincial formularies. Note that the 1800 estimate is an upper bound of the actual loss due to informational channels because the central government

should have at least the same amount of information as us.

Unfortunately, due to our data limit, we are not able to tighten the bounds of the welfare estimates further. These back-of-the-envelope estimates highlight that the local distortion concern is much larger than the heterogeneous preference concern, while the final welfare comparison of a centralized national uniform formulary relative to a decentralized provincial formulary depends on the extent of the informational advantage of local governments. There is an ongoing policy change to transfer public insurance claims data to the National Health Insurance Administration and establish a centralized medical database in China. If such policies are implemented, we expect the informational advantage of provincial governments to decay over time.

6 Conclusion

In this paper, we document how provincial governments use the public insurance drug formulary design to favor local firms. We find that provincial governments are more likely to cover a drug if there is at least one local manufacturer producing it, holding the demand fixed. We use a stylized model to highlight the trade-off between a national single formulary and provincial formularies: the former corrects the distorted incentives of provincial governments but may not account for heterogeneous demand and use less accurate information.

One limitation of our paper is that we do not account for all kinds of private incentives faced by provincial governments. Many of these incentives are hidden from the public and hard to verify with data. Still, there is room for more creative ways to document such behaviors. Future research is needed in this area.

Our empirical analysis suggests that the distortion in decentralized policy-making could be sizable, often overturning the benefits of local governments' informational advantage on heterogeneous preferences and freedom to establish province-specific formularies. These results lend support to a series of recent policy changes in China that transfer the managerial obligation of the social insurance system from provincial or even sub-provincial governments to the central government. More research is needed to evaluate the trade-off and welfare consequence of these other policies outside of the context of the drug formulary design.

References

Bai, Chong-En, Zhigang Tao, and Yueting Sarah Tong. 2008. "Bureaucratic Integration and Regional Specialization in China." *China Economic Review*, 19(2): 308–319.

Bai, Jie, Shanjun Li, Danxia Xie, and Hui Zhou. 2021. "Environmental Protection or Environmental Protectionism? Evidence from Tail Pipe Emission Standards in China." *AEA Papers and Proceedings*, 111: 381–385.

Bardhan, Pranab, and Dilip Mookherjee. 2000. "Capture and Governance at Local and National Levels." *American Economic Review*, 90(2): 135–139.

Barwick, Panle Jia, Shengmao Cao, and Shanjun Li. 2021. "Local Protectionism, Market Structure, and Social Welfare: China's Automobile Market." *American Economic Journal: Economic Policy*, 13(4): 112–151.

Chen, Lian, and Li Han. 2023. "Pills and Power: Political Connections and Medical Insurance Drug Formulary in China." Working Paper.

Costinot, Arnaud, Dave Donaldson, Margaret Kyle, and Heidi Williams. 2019. "The More We Die, The More We Sell? A Simple Test of the Home-Market Effect." *The Quarterly Journal of Economics*, 134(2): 843–894.

Dubois, Pierre, and Laura Lasio. 2018. "Identifying Industry Margins with Price Constraints: Structural Estimation on Pharmaceuticals." *American Economic Review*, 108(12): 3685–3724.

Duggan, Mark, and Fiona Scott Morton. 2010. "The Effect of Medicare Part D on Pharmaceutical Prices and Utilization." *American Economic Review*, 100(1): 590–607.

Fang, Hanming, Ming Li, and Zenan Wu. 2022. "The Downside of Tournament-Style Political Competition: Evidence from China."

Geruso, Michael, Timothy Layton, and Daniel Prinz. 2019. "Screening in Contract Design: Evidence from the ACA Health Insurance Exchanges." *American Economic Journal: Economic Policy*, 11(2): 64–107.

He, Guojun, Shaoda Wang, and Bing Zhang. 2020. "Watering Down Environmental Regulation in China." *The Quarterly Journal of Economics*, 135(4): 2135–2185.

He, Guojun, Yuhang Pan, and Yang Xie. 2023. "Market vs. Planning: Emission Abatement under Incomplete Information and with Local Externalities." Working Paper.

Huang, Zhangkai, Lixing Li, Guangrong Ma, and Lixin Colin Xu. 2017. "Hayek, Local Information, and Commanding Heights: Decentralizing State-Owned Enterprises in China." *American Economic Review*, 107(8): 2455–2478.

Kanavos, Panos, Mackenzie Mills, and Anwen Zhang. 2019. "Pharmaceutical Policy in China." London School of Economics.

Lavetti, Kurt, and Kosali Simon. 2018. "Strategic Formulary Design in Medicare Part D Plans." *American Economic Journal: Economic Policy*, 10(3): 154–192.

Liu, Ernest, Yi Lu, Wenwei Peng, and Shaoda Wang. 2023. "Court Capture, Local Protectionism, and Economic Integration: Evidence from China."

Ogawa, Hikaru, and David E Wildasin. 2009. "Think Locally, Act Locally: Spillovers, Spillbacks, and Efficient Decentralized Policymaking." *American Economic Review*, 99(4): 1206–1217.

Persaud, Nav, Maggie Jiang, Roha Shaikh, Anjli Bali, Efosa Oronsaye, Hannah Woods, Gregory Drozdzal, Yathavan Rajakulasingam, Darshanand Maraj, Sapna Wadhawan, Norman Umali, Ri Wang, Marcy McCall, Jeffrey K Aronson, Annette Plüddemann, Lorenzo Moja, Nicola Magrini, and Carl Heneghan. 2019. "Comparison of Essential Medicines Lists in 137 Countries." *Bulletin of the World Health Organization*, 97(6): 394–404C.

Song, Yining. 2019. "Whose Interests Are Affected by the Three-Year Phase-out of Provincial Drug Formularies?" *https://www.yyjjb.com.cn/yyjjb/201909/20190904121933193 3_5427.shtml*.

Tarricone, Rosanna, Fabio Amatucci, Patrizio Armeni, Helen Banks, Ludovica Borsoi, Giuditta Callea, Oriana Ciani, Francesco Costa, Carlo Federici, Aleksandra Torbica, and Marcella Marletta. 2021. "Establishing A National HTA Program for Medical Devices in Italy: Overhauling a Fragmented System to Ensure Value and Equal Access to New Medical Technologies." *Health Policy*, 125(5): 602–608.

Wang, Chao, Qing Li, Arthur Sweetman, and Jeremiah Hurley. 2015. "Mandatory Universal Drug Plan, Access to Health Care and Health: Evidence from Canada." *Journal of Health Economics*, 44: 80–96.

Young, Alwyn. 2000. "The Razor's Edge: Distortions and Incremental Reform in the People's Republic of China." *The Quarterly Journal of Economics*, 115(4): 1091–1135.

Zhang, Xuan, and Huihua Nie. 2021. "Public Health Insurance and Pharmaceutical Innovation: Evidence from China." *Journal of Development Economics*, 148: 102578.

Appendix A. Supplementary Tables and Figures

Table A1: List of Provinces with Drug Formulary Data

Province	Year		
	2005	2009	2017
Anhui	N	Y	Y
Beijing	N	Y	Y
Chongqing	Y	Y	N
Fujian	N	Y	Y
Gansu	N	Y	Y
Guangdong	N	Y	N
Guangxi	Y	Y	Y
Guizhou	N	Y	Y
Hainan	Y	Y	N
Hebei	Y	Y	Y
Henan	N	Y	Y
Heilongjiang	Y	Y	Y
Hubei	Y	Y	Y
Hunan	Y	Y	Y
Inner Mongolia	Y	Y	N
Jiangsu	Y	Y	Y
Jiangxi	Y	Y	Y
Jilin	Y	Y	Y
Liaoning	Y	Y	Y
Ningxia	Y	Y	Y
Qinghai	Y	Y	Y
Shaanxi	N	Y	N
Shandong	Y	Y	Y
Shanghai	Y	Y	Y
Shanxi	N	Y	N
Sichuan	N	Y	Y
Tianjin	Y	Y	N
Tibet	Y	Y	Y
Xinjiang	Y	Y	Y
Yunnan	Y	Y	Y
Zhejiang	Y	Y	N

Notes: This table lists the provinces with available data on Provincial Catalog B.

Table A2: The Effects of The Residual of The Past Disease Prevalence

	(1) Presence of Local Firms in 2005-2008	(2) Number of Local Firms in 2005-2008	(3) Presence of Local Firms in 2016	(4) Number of Local Firms in 2016	(5) Presence of Non-Local Firms in 2016	(6) Number of Non-Local Firms in 2016
Residual of disease prevalence in 2005	0.0119***	0.0094***	0.1388***	0.0076**	0.0001	0.0000
	(0.0025)	(0.0017)	(0.0016)	(0.0031)	(0.0031)	(0.0047)
Observations	38,037	38,037	38,037	38,037	38,037	38,037
Drug FE	Y	Y	Y	Y	Y	Y
ATC4×Province FE	Y	Y	Y	Y	Y	Y
R^2	0.0174	0.0115	0.0166	0.0150	0.0064	0.0050
Adj. R^2	0.0186	0.0126	0.0299	0.0197	0.0078	0.0062

Notes: This table employs drug-province level data to examine the effects of the residual of the past disease prevalence on the presence of local and non-local firms producing corresponding treating drugs in the short (2005-2008) and long run (2016). The residual is estimated by running a regression of the provincial disease prevalence in 2005 on the prevalence in 2016. We then match the residual of the past disease prevalence with the drugs based on the drug indication information from the drug registration data. The presence of local (non-local) firms is measured as whether there are any or the number of local (non-local) firms producing (selling) the drug treating the disease in the province. Standard errors are two-way clustered at the disease and province levels and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Local Firm and Formulary Design

	OLS	Reduced Form	First Stage	IV
	(1)	(2)	(3)	(4)
	Covered by Insurance	Covered by Insurance	Presence of Local Firms	Covered by Insurance
Presence of Local Firms in 2016	0.045***			0.092***
	(0.007)			(0.013)
Instrument		0.003***	0.032***	
		(0.001)	(0.010)	
Observations	38,037	38,037	38,037	38,037
Drug FE	Y	Y	Y	Y
Disease×Province FE	Y	Y	Y	Y
R^2	0.128	0.127	0.198	0.191
Adj. R^2	0.143	0.142	0.214	0.207
F test:			37.264	

Notes: This table presents baseline results controlling for disease by province fixed effects. We use the baseline sample in the 2017 formulary version, and hence, each observation is a drug by province. "Presence of Local Firms in 2016" is a dummy variable indicating whether there was at least one local firm producing the corresponding drug in the year before the formulary change in 2017. "Instrument" is an instrumental variable constructed by predicting the part of the local prevalence of diseases that the corresponding drug treats in 2005 that cannot affect the local prevalence in 2016. Please see the context for the details. Standard errors are two-way clustered at the drug and province levels and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Robustness Check: Local Firm and Formulary Design in 2009 Formulary Version

	OLS	Reduced Form	First Stage	IV
	(1)	(2)	(3)	(4)
	Covered by Insurance	Covered by Insurance	Presence of Local Firms	Covered by Insurance
Presence of Local Firm in 2008	0.040***			0.037***
	(0.004)			(0.006)
Instrument		0.006***	0.172***	
		(0.001)	(0.017)	
Observations	51,350	51,350	51,350	51,350
Drug FE	Y	Y	Y	Y
ATC4×Province FE	Y	Y	Y	Y
R^2	0.198	0.191	0.165	0.119
Adj. R^2	0.214	0.207	0.181	0.134
F test			44.295	

Notes: This table shows robust results using the baseline sample in the 2009 formulary version. Hence, each observation is a drug by province. "Presence of Local Firm in 2008" is a dummy variable indicating whether there was at least one local firm producing the corresponding drug in the year before the formulary was published in 2009. "Instrument" is an instrumental variable constructed by predicting the part of the local prevalence of diseases that the corresponding drug treats in 2005 that cannot affect the prevalence in 2008. Please see the context for the details. Standard errors are two-way clustered at the drug and province levels and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Robustness Check: Alternative Regressor and Alternative Controls

	(1)	(2)	(3)	(4)
	Covered by Insurance	Covered by Insurance	Covered by Insurance	Covered by Insurance
Presence of Local Firm in 2016	0.036***	0.038***		
	(0.004)	(0.009)		
Number of Local Firms in 2016			0.010***	0.017**
			(0.003)	(0.008)
Observations	38,037	38,037	38,037	38,037
Drug FE	Y	Y	Y	Y
ATC4×Province FE	Y	N	Y	N
ATC3×Province FE	N	Y	N	Y
R^2	0.128	0.127	0.198	0.191
Adj. R^2	0.143	0.142	0.214	0.207
First Stage F-test	36.526	40.150	29.099	31.072

Notes: This table shows robust results using the number of local firms producing the corresponding drug one year before the formulary change in 2017 as the regressor of interest or/and controlling ATC 3 by province fixed effects. We use the baseline sample in the 2017 formulary version, and hence, each observation is a drug by province. "Presence of Local Firm in 2016" is a dummy variable indicating whether there was at least one local firm producing the corresponding drug in the year before the formulary was published in 2017. "Number of Local Firms in 2016" indicates the number of local firms producing the corresponding drug in the year before the formulary was published in 2017. Columns (1) and (3) show the 2SLS estimates controlling for ATC 4 by province fixed effects; columns (2) and (4) show the 2SLS estimates controlling for ATC 3 by province fixed effects. Please see the context for the details of the construction of the instrument variable. Standard errors are two-way clustered at the drug and province levels and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Robustness Checks: Alternative Tax Contribution Measurement

	Tax Contribution Share		Local Tax Contribution		Income Tax Contribution from SAT		Income Tax Contribution from ASIF	
	above median	below median	above median	below median	above median	below median	above median	below median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Presence of Local Firms in 2016	0.038**	0.029*	0.041**	0.021*	0.040***	0.027**	0.039***	0.028**
	(0.015)	(0.015)	(0.020)	(0.011)	(0.009)	(0.011)	(0.012)	(0.013)
Observations	29,026	29,026	29,026	29,026	29,026	29,026	29,026	29,026
Drug FE	Y	Y	Y	Y	Y	Y	Y	Y
ATC4×Province FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.1880	0.1868	0.1666	0.1701	0.1758	0.1742	0.1769	0.1798
Adj. R^2	0.1901	0.1971	0.1694	0.1722	0.1803	0.1799	0.1826	0.1830
First Stage F-test	41.169	29.561	47.306	18.061	38.738	33.652	39.179	34.115

Notes: This table shows robust results using alternative tax contribution measurement. Columns (1) and (2) employ tax contribution share, which is calculated as the ratio of the tax paid by local firms producing the corresponding drug in the corresponding province divided by the tax paid by all firms in the province; columns (3) and (4) employ local tax contribution amount; columns (5) and (6) employ income tax contribution amount calculated from SAT; columns (7) and (8) employ income tax contribution amount calculated from ASIF. We use the baseline sample in the 2017 formulary version, and hence, each observation is a drug by province. Columns (1), (3), (5), and (7) ((2), (4), (6), and (8)) present the 2SLS estimates in the subsample—each consisting of non-local drug-province observations and local drug-province observations whose producers have a corresponding characteristic above(below) the median across all observations. Please see the context for the details of the construction of the instrument variable. Standard errors are two-way clustered at the drug and province level and are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B. Calculation Details of the Welfare Analysis

Let e_{dp} be a random variable i.i.d. with a standard normal distribution. Define $G(a) \equiv E(e_{dp}|e_{dp} > a) = \frac{\phi(a)}{1-\Phi(a)}$, where $\phi(\cdot)$ is the probability density function of the standard normal distribution, and $\Phi(\cdot)$ is the cumulative density function. Let $\hat{\delta}_{dp}$ and $\hat{\Delta}_{dp}$ denote our estimates of δ_{dp} and Δ_{dp} from the probit model.

When $e = \varepsilon$, we have:

$$W_0 = \mathbb{E}\left[\sum_d \sum_p (\hat{\delta}_{dp} + \varepsilon_{dp}) \mathbb{1}(\hat{\delta}_{dp} + \varepsilon_{dp} > 0)\right] \tag{1}$$

$$= \sum_d \sum_p \mathbb{E}\left[(\hat{\delta}_{dp} + \varepsilon_{dp}) \mathbb{1}(\hat{\delta}_{dp} + \varepsilon_{dp} > 0)\right] \tag{2}$$

$$= \sum_d \sum_p \left(\hat{\delta}_{dp}\Phi(\hat{\delta}_{dp}) + G(-\hat{\delta}_{dp})\right), \tag{3}$$

$$W_1 = \sum_d \sum_p \left(\hat{\delta}_{dp} \mathbb{1}(\hat{\delta}_{dp} > 0)\right), \tag{4}$$

$$W_2 = \sum_d \sum_p \left(\hat{\delta}_{dp} \mathbb{1}(\sum_p \hat{\delta}_{dp} > 0)\right), \tag{5}$$

$$W_3 = \sum_d \sum_p \left(\hat{\delta}_{dp}\Phi(\hat{\delta}_{dp} + \hat{\Delta}_{dp}) + G(-\hat{\delta}_{dp} - \hat{\Delta}_{dp})\right). \tag{6}$$

When $e_{dp} = \omega_{dp}$, we have:

$$W_0 = \sum_d \sum_p \left(\hat{\delta}_{dp} \mathbb{1}(\hat{\delta}_{dp} > 0)\right), \tag{7}$$

$$W_1 = \sum_d \sum_p \left(\hat{\delta}_{dp} \mathbb{1}(\hat{\delta}_{dp} > 0)\right), \tag{8}$$

$$W_2 = \sum_d \sum_p \left(\hat{\delta}_{dp} \mathbb{1}(\sum_p \hat{\delta}_{dp} > 0)\right), \tag{9}$$

$$W_3 = \sum_d \sum_p \left(\hat{\delta}_{dp}\Phi(\hat{\delta}_{dp} + \hat{\Delta}_{dp})\right). \tag{10}$$