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RESEARCH ARTICLE

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A structural analysis of physician agency and pharmaceutical demand

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Abstract

This paper examines the significance of physician agency in medical providers' prescription choices. Physician agency is considered as medical providers' responses to the price and markup percentage of prescription drugs. Their preferences are allowed to be heterogeneous using a random coefficient logit model. Using a sample of anti-diabetic prescriptions with metformin from a population-based database in Taiwan, empirical results reveal that physician owners, privately-owned medical providers, small medical providers and the medical providers facing less competition are more likely to prescribe drugs with higher profit margins. The aggregate pharmaceutical demand is also found to increase with the markup, which is allowed to be endogenous in the estimation. Price elasticity estimates suggest medical providers are quite responsive to pharmaceutical price changes in Taiwan. Counterfactual analysis reveals the potential impact of physician agency is economically significant. Removing markups and lowering pharmaceutical prices are found to be more welfare enhancing than restricting physicians' dispensing services.

KEYWORDS
diabetes, pharmaceutical demand, physician agency, structural analysis

JEL CLASSIFICATION
D82, I11, I18

1 | INTRODUCTION

During the summer of 2016, Tzu Chi General Hospital, a major hospital chain in Taiwan with six branches and 3300 beds, planned to replace the 135 brand-name drugs on their formulary to generic ones. Their agenda unexpectedly caught the media's attention due to a leaked internal document prepared for pharmaceutical bidders, which mentions that their drug selection criteria “do not consider the professional feedbacks [from doctors] such as patients' reactions to the drugs or the drug efficacy.” The document states that the main criteria are to select the drugs (1) with the highest differences between reimbursed price and acquisition price; (2) adopted by at least one academic medical center; and (3) earning profits equal to or greater than New Taiwan Dollar (NT$) 100,000 for the chain.[1]

This profit-oriented choice of drugs highlights the physician agency problem in the pharmaceutical markets in Taiwan. Profit margin and competition with the other medical providers seems to be more important than patients' recovery in providers' prescription decisions. Similar stories were also found in the United States. For example, Meier and Thomas of *The New York Times* (2012) reported that insurers pay substantially high markups when physicians dispense drugs in their offices.[2] Medical providers were also found to respond to financial incentives when making prescription choices in countries like Sweden (Lundin, 2000), Japan (Iizuka, 2012), China (Lu, 2014; Wu, 2019), United Kingdom (Goldacre et al., 2019) and Switzerland

(Burkhard et al., 2019). But Crea et al. (2019) found providers' habits in prescribing brand-name drugs better explained their prescription choices than either physician altruism or agency in Norway. Most of these papers focus on physicians' dichotomous choices between brand-name drugs and generics.[3]

This paper contributes to the extensive literature on physician agency by proposing a discrete choice model that allows providers to choose from a set of drugs with potential agency concerns. The model considers both medical providers' attributes and the drug characteristics. Information on pharmaceutical price and markup of each drug is also included in the analysis, which is rarely found in the existing literature. Empirical results provide estimates on the marginal and welfare effects of physician agency, and coefficient estimates on the pharmaceutical demand curve and price elasticity. These estimates enable comparisons between various policies toward regulating physician agency.

Liu et al. (2009) studied physician agency in Taiwan. This paper extends their work by using a structural analysis that allows counterfactual estimates for potential policy effects. This paper also extends their measure of physician agency by calculating the average markup of each drug. Iizuka (2012) also studied the effect of pharmaceutical markup on clinic physicians' brand-name drug adoptions in Japan. This paper extends Iizuka's (2012) work by investigating physicians' multiple choices of their prescription decisions, and using data from both hospitals and clinics. The results of this paper are also suggestive to other countries that allow pharmaceutical promotions such as detailing and advertising. For example, Engelberg et al. (2014) found a positive relationship between pharmaceutical providers' payments to physicians and physicians' prescriptions of the associated drugs.

Physicians' prescription decision process is modeled in this paper as a utility maximization decision based on the characteristics of patients, medical providers, and drugs. Using the detailed patient-level information from the U.S. market of statins, Dunn (2012) demonstrated that individual information can be incorporated into the pharmaceutical demand estimation with the framework proposed by Berry et al. (2004), (hereafter MicroBLP). This paper extends Dunn's (2012) method by incorporating physician agency into pharmaceutical demand, which was not considered in Dunn (2012). I used a random coefficient logit model to allow providers' preferences toward financial incentives from prescription drugs to be heterogeneous. Pharmaceutical price and markup are interacted with physicians' characteristics that likely affect their prescription decisions, including their ownership of the hospitals and clinics, whether they dispensed drugs, and their experience level. Other medical provider characteristics modeled as sources of physician agency include public ownership, competition from other providers in the same market and the accreditation level that measures the size of a medical provider by its number of beds. These factors that affect providers' financial incentives but not patients' health outcomes capture the supplier-induced demand, which is defined as the demand that was shifted in the physician's interest but not for the patient's utility (Sloan and Hsieh, 2017).

Empirical results reveal that physician owners, privately-owned medical providers, small medical providers and the medical providers facing less competition are more likely to prescribe drugs with higher profit margins. Physician dispensers are more likely to prescribe more expensive drugs. These estimates reveal significant agency effects, as a perfect agent would not consider these factors when prescribing drugs. While these heterogeneity effects could be endogenously determined, controlling for these effects allows for the estimation of common demand among the providers for subsequent analyses.

The coefficient estimates reported above were then used for a two-stage least squares (TSLS) regression to estimate the demand curve of the prescription drugs. The markup of these drugs is allowed to be endogenous with the demand. The pharmaceutical demand was found to increase with markup and decrease with price, which is the main finding of this paper. The results also show that the providers' demand for diabetic drugs in the Taiwanese market is price elastic; the average estimate is −2.34.

Counterfactual analysis shows that policies regulating the price and markup percentage of drugs could be welfare enhancing for patients by eliminating the financial incentives for medical providers. The estimates show that a policy implemented in Taiwan in 2014 could increase the joint surplus of patients and providers by as much as US$14.05 million. As providers acquired no profits from this policy, most of the benefits were for patients. The analysis also reveals that restricting physicians' dispensing services could lower the joint surplus of providers and patients by about US$9 million. The results reveal that removing markups and lowering pharmaceutical prices are more welfare enhancing than restricting physicians' dispensing services. The actual impact of physician agency is certainly larger than what is reported in this paper, as the sample covers only 33 drugs while there were 1144 diabetic drugs and a total of 43,661 drugs covered by the National Health Insurance (NHI) in Taiwan in 2021.

This paper contributes to the literature by separating the effects of provider heterogeneity and profit margin of a drug from the other determinants. Chandra et al. (2012) proposed a theoretical framework that considers a physician's utility from a prescription to include the benefit to the patient, the physician's financial incentives and physician heterogeneity. While the existing literature has found empirical support for these aspects, it is common to have the effect of one factor mixed with another. For example, a patient's insurance status could affect both her benefits and the physician's financial incentives. A study of countries with multiple insurance providers would also have to consider insurer heterogeneity that could affect both patients and physicians.[4] The institutional and empirical settings of this paper alleviate these concerns. Since this paper covers only drugs with metformin that are often prescribed for patients in the early stage of diabetes, patients' benefits from treatments are similar across the available choices. As the patients' insurance statuses are the same under the universal healthcare system in Taiwan, their copayments are also similar across the prescription drugs. These settings allow this paper to focus on the supply-side determinants of physicians' prescription choices.

The empirical analysis also held the effects of the payment system and fee structure on physicians to be similar across prescription choices because almost all the physicians in Taiwan are contracted and regulated under Taiwan's single payer system. As the providers are allowed to both prescribe and dispense drugs in Taiwan, their financial incentives behind each prescription choice mainly lies on the profit margin of a drug. These institutional and empirical settings thus enable the empirical analysis to focus on the effects of physicians' heterogeneity and profit margin of a drug on their choices of prescription drugs. The resulting counterfactual estimates, backed by the ample details from the rich dataset, contribute to the literature by quantifying the size of physician agency in pharmaceutical demand.[5]

The remainder of the paper is organized as follows. The next section describes the background information of the Taiwanese health care system. Section 3 provides the details of the data and summary statistics. The empirical model is proposed in Section 4. Empirical results are reported in Section 5. Section 6 discusses the results from counterfactual analysis. Section 7 concludes this paper.

2 | BACKGROUND

2.1 | National health insurance in Taiwan

Taiwan implements a single payer, universal health care system similar to Canada. The health insurance system is administrated by the National Health Insurance Administration, Ministry of Health and Welfare (NHIA). Most of the medical providers provide health care services under contract with the NHIA. Patients pay premiums each month, conditional on their salary and dependencies, and they pay roughly 15% of their medical expenses in each outpatient visit to a doctor. For each patient visit, medical providers file a claim that records the diagnoses and treatments for the patient. Associated fees are regulated by the NHIA, such as the service fees for doctors and pharmacists, and they are also recorded in the claim. Information regarding each prescription drug is recorded as separate logs associated with the claim, including the price of the drug, the number of days for the prescription, and the number of units prescribed. The claim is then used to apply for reimbursement from the NHIA.

Physicians in Taiwan are either employed or employers in hospitals or clinics; about two-thirds of physicians were employed (Lu and Hsiao, 2003). In the rest of the paper, I considered a physician as an owner if she was marked as legally obliged for her practicing facility in the basic information file in the National Health Insurance Research Database (NHIRD). Tang and Wu (2020) discussed in length about the incentive structure of the physicians in hospitals and clinics in Taiwan. While clinic owners are obviously responsive to their financial incentives, Cheng (2003) mentioned that most hospitals in Taiwan also provide their staff physicians incentives to generate more revenues. In particular, Cheng (2003) described a professional fee system adopted by some hospitals in Taiwan that compensate physicians based on their revenue productivity, such as the number of patients seen and the procedures performed. Bennett et al. (2015) compared the system used in Taiwan to the staff model HMO in the United States. Accordingly, while hospitals negotiated their formulary with pharmaceutical firms, physician-staffs were encouraged to prescribe more of the drugs the hospitals negotiated. The prescription choices made by these physicians thus reflected the preferences of the hospitals.

In response to rising drug expenditures, the Taiwanese government launched a "separating policy" in 1997 that prohibits physicians in clinics to both prescribe and dispense drugs in two major cities in Taiwan, Taipei and Kaohsiung. The policy was then implemented nationwide in 2003. But on-site pharmacies in clinics with licensed pharmacists were allowed to continue to dispense drugs, which is similar to the safe harbor exception of the Stark Law in the United States (Chen et al., 2013). Many on-site pharmacies were open in response to this exemption of the policy. Many "gateway pharmacies" were also opened by or integrated with the clinics next door. Thus, most physicians in clinics continued to have the same financial incentives related to prescriptions after the implementation of the separating policy.

In the NHIRD, each claim marks whether a prescription was released for the patient to purchase drugs from pharmacies. It is likely that the profit margin still went to the physician who gave the prescription. In the rest of the paper, I considered a prescription marked as "not released" to be prescribed by a physician who both prescribed and dispensed drugs, a physician dispenser, but the true proportion of these physician dispensers could be higher. Most of the related studies stress on the markets where physicians can both prescribe and dispense drugs, including the Japanese market (Iizuka, 2007, 2012), Taiwanese market (Liu et al., 2009), and Chinese market (Lu, 2014).

Similar to Germany, the NHIA adopts a global budgeting system with retrospective payments. Global budgeting was implemented separately for four sectors in Taiwan, including dentistry in 1998, Chinese medicine in 2000, community clinics in 2001, and hospitals in 2002. The last two sectors separate physicians practicing Western medicine into two separate caps; thus, hospitals and clinics compete in the same market but under separate budgets. Providers are paid by fee-for-service under the global budgeting system, but the service price is calculated by points instead of a dollar amount. The actual amount reimbursed for each service depends on the final point value that is calculated by dividing the predetermined budget by the total service amount. The point value can be larger or lower than NT$1; however, pharmaceutical reimbursements are not discounted in the same manner and maintain a monetary value of NT$1. Chou et al. (2020) documented that the providers responded to the global budgeting system in Taiwan by prescribing more drugs because the dollar value of drug expenses was not affected by the implementation of the global budgeting system. The average point value during the sampling period for the two sectors covered in this paper, hospitals from 2002 and clinics from 2001, is NT$0.8794.

The background information reveals the advantages to study physician agency in this system: First, medical providers have strong financial incentives in Taiwan since they are allowed to both prescribe and dispense drugs. Most of the related studies stress on the markets with this feature, including the Japanese market (Iizuka, 2007, 2012), Taiwanese market (Liu et al., 2009), and Chinese market (Lu, 2014). Second, the universal coverage in Taiwan avoids the selection problem in the data from countries with multiple payers, such as Coey's (2015) focus on the U.S. market. As more than 100 countries around the world are pursuing universal health care coverage for their citizens,[6] the results of this paper would be suggestive to these countries regarding the regulations of pharmaceutical markets under a universal health care system.

2.2 | Pricing and markup under the national health insurance in Taiwan

The NHIA determines the drugs covered by the insurance and maintains a reimbursement formulary. As a drug entered the reimbursement formulary, its launch price was determined by its therapeutic value and the price listed in other countries.[7] While the reimbursement prices of the covered drugs are regulated, medical providers are allowed to negotiate procurement prices with pharmaceutical providers. On a yearly basis, the NHIA regularly surveys pharmaceutical providers and medical providers on their privately-negotiated procurement prices of drugs. While the survey results were not revealed to the public, the average of these procurement prices was used to adjust the reimbursement prices of these drugs.

Specifically, denote the average of the reported procurement prices for drug j at time t as $\overline{P^p_{jt}}$ and the regulated price of drug j at time t as P^r_{jt}. The average markup received from prescribing drug j is then $P^r_{jt} - \overline{P^p_{jt}}$. The NHIA regulated this markup to be within 16% of the price P^r_{jt}, which is called a "reasonable zone" for providers to make profits from prescription drugs. The pricing formula is then set by comparing the sizes of the reported average markup and the reasonable zone as follows. If $P^r_{jt} - \overline{P^p_{jt}} \leq 0.16 \times P^r_{jt}$, meaning the average markup is no greater than 16% of the regulated price, then the price for the next period would not be adjusted, $P^r_{jt+1} = P^r_{jt}$; if $P^r_{jt} - \overline{P^p_{jt}} > 0.16 \times P^r_{jt}$, meaning the average markup exceeds the reasonable zone, then the price in period $t+1$ would be brought down to the level that equals the sum of the average procurement price in period t and 16% of the period t price as follows:

$$P^r_{jt+1} = \overline{P^p_{jt}} + 0.16 \times P^r_{jt}, \tag{1}$$

which would bring down the average markup to be no larger than the reasonable zone. This also implies that a higher markup in time t is related with a lower price in $t+1$. Thus, the average price and markup across time are expected to be negatively correlated.

While only the regulated pharmaceutical price change for a drug is publicly observed, the presence or absence of a price adjustment by the NHIA in period $t+1$ can be used to derive a drug's procurement price and thus markup in period t based on the above discussion. In particular, if a drug's reimbursement price was changed in time $t+1$, the unobserved $\overline{P^p_{jt}}$ and the markup $P^r_{jt} - \overline{P^p_{jt}}$ can be derived from the observed P^r_{jt} and P^r_{jt+1} using Equation (1); if the price remained unchanged in period $t+1$, the markup is assumed to be at its maximum, $0.16 \times P^r_{jt}$. While the true markup could be smaller than this value, this assumption allows estimation on the upper bound of physician agency. The markup of each drug j was thus calculated as follows:

$$M_{jt} = \begin{cases} 0.16 \times P^r_{jt} & \text{if } P^r_{jt+1} = P^r_{jt} \\ P^r_{jt} - \overline{P^p_{jt}} & \text{if } P^r_{jt+1} \neq P^r_{jt}. \end{cases} \tag{2}$$

During the sample period from 1999 to 2008, there were seven price adjustments by the NHIA; the price adjustments were implemented on the first day of the following months: April 2000, April 2001, March 2003, November 2004, September 2005, November 2006 and September 2007. Price adjustment results in October 2009 were also used to calculate markups. If a drug's price was adjusted at times other than the announced price adjustment dates, the price change was considered to provide no information on the procurement price. The adjustment was likely due to an individual contract signed between the NHI and a pharmaceutical provider that links the price with international ones and thus provide no information on markup.[8]

The NHIA pricing formula was adopted from the Japanese system mentioned in Iizuka (2012). While Iizuka (2012) also inferred the mean of physicians' markups from pharmaceuticals in Japan and studied their effect, his sample includes only the data from clinics to account for the possibility that hospitals were more heterogeneous in bargaining power than the clinics. Because the Taiwanese data include the characteristics of physicians and medical institutions, these characteristics were used in the regressions to distinguish the heterogeneous effect from the observed markup. This paper also extends Iizuka (2012) by investigating the static multiple choices of physicians, while Iizuka (2012) focused on the dichotomous choices between generic and branded drugs with dynamic considerations. This allows for counterfactual analysis on the welfare effects of physician agency.[9]

3 | DATA

3.1 | Data descriptions

The sample analyzed in this paper was obtained from the NHIRD of Taiwan. The database contains population data covering nearly all the Taiwanese citizens under universal coverage; the population in Taiwan was about 23.85 million people in 2021. The database consists of monthly claims information filed by medical providers for reimbursement from the NHIA. The sample was collected from a subset of the NHIRD, the Longitudinal Cohort of Diabetes Patients, which samples from all the medical records of the patients with diabetes. Liu et al. (2009) mentioned three advantages of focusing on diabetes drugs in the Taiwanese market: First, diabetes is a prevalent chronic disease in Taiwan and accounts for a large share of the health care expenditure. Second, the therapeutic market for oral hypoglycemic agents (OHAs) is highly competitive. Pharmaceutical providers might compete to be included in a medical provider's formulary by offering a more favorable discount rate. Third, the branded and generic OHAs are quite diverse in regard to therapeutic class. Therefore, this paper focuses on the diabetic prescriptions in Taiwan.

Roughly 160,000 to 190,000 new diabetes patients appeared in the NHIRD every year during 1997 to 2011. The total number of diabetes patients in Taiwan from 1997 to 2011 is about 3 million patients. In each year, the NHIRD sampled 120,000 patients and divided them equally into three groups. I purchased one group of data and used their medical records from each year from 1999 to 2008 for analysis. The data include full medical histories of the diabetes patients in the sample, but only the records related to diabetes were considered in the analysis.[10]

This paper focuses on physicians' prescription choices among available OHAs reimbursed by the NHIA. Each claim in the sample records the prescribed drug and the associated fees. Information related to the claim, including the characteristics of the prescribed drug, patient, physician and facility were merged from the other datasets of the NHIRD. Information on the drugs, including names, the history of regulated prices, the date a drug entered the formulary, forms and packages, whether a drug is imported or produced by outsourcing manufacturers, and branded or generic version, was obtained from the website of the NHIA.[11] Information on whether a pharmaceutical producer was listed in the Taiwanese stock market is also included in the analysis. In addition, market characteristics of each medical provider were collected from government websites.[12] The market is defined at the district/township/village level in Taiwan; In total there are 340 markets in the sample. The NHIA divides these markets into six branches by closeness for management and budgeting purposes.

3.2 | Summary statistics

This paper focuses on doctors' choices concerning drugs with metformin, which is the recommended prescription for patients who are in the early stage of diabetes. These patients' situations are less complicated, and the generic options with metformin in the formulary were abundant. Focusing on drugs with only one chemical substance also allows the brand-name drug with metformin, Glucophage, to be a natural outside option in the empirical model.

Table 1 lists the information on the 33 drugs included in the choice set for the providers. Only drugs that came in 500 mg pills were included in the analysis; they account for more than 93% of the original sample. Five drugs that were prescribed fewer than 30 times during the sampling period were also dropped because drugs that were rarely chosen would prevent convergence of the estimation. Other drugs were prescribed more than 10,000 times on average. The drugs with both original and aluminum packaging are listed twice; the aluminum packaging was introduced much later in the sample. Because both packages of

TABLE 1 Summary statistics of the oral hypoglycemic agents in the sample.

Product	Number of Prescriptions	Mean price Per DDD	Mean markup Percentage of price	Number of Months	Import	Aluminum	Stock
GLUCOPHAGE[B]	23,267	2.800 (0.611)	28.837 (12.862)	120	FRANCE		
GLIBUDON	12,774	2.408 (0.607)	28.460 (10.795)	120			
GLIBUDON	1166	1.5 (0)	15 (0)	13		X	
GLUCOMINE	9507	2.538 (0.540)	28.427 (11.521)	120			
DIAFORMIN	8896	2.414 (0.443)	26.985 (11.797)	118	AUSTRALIA		
METFORMIN	7426	2.572 (0.495)	27.609 (13.452)	118	UNITED KINGDOM		
LODITON	6264	2.325 (0.573)	31.200 (11.259)	98			X
LODITON	352	1.5 (0)	15 (0)	14		X	X
BENTOMIN	6195	2.494 (0.594)	28.422 (12.339)	111			
VOLV	5570	2.442 (0.522)	26.539 (10.360)	120			X
VOLV	609	1.5 (0)	15 (0)	14		X	X
METFORMIN(KINGDOM)	4770	2.430 (0.567)	28.884 (10.580)	117			
METFORMIN(KINGDOM)	286	1.5 (0)	15 (0)	14		X	
UFORMIN	4036	2.264 (0.562)	29.528 (12.227)	86			X
UFORMIN	209	1.5 (0)	15 (0)	12		X	X
GLUBIN	3525	2.458 (0.537)	28.991 (12.384)	119			
GLUCOFIT	3373	2.589 (0.526)	28.085 (12.610)	119			
MEGLUMINE	2491	2.433 (0.413)	25.083 (10.414)	110			
LIAL	1876	2.205 (0.388)	27.561 (10.939)	118			
METFORMIN(S.F.)[O]	1151	2.423 (0.432)	24.750 (10.311)	98			
BICANOL	716	2.427 (0.381)	24.605 (10.937)	96			
METFORMIN(LITA)	466	2.601 (0.231)	20.592 (6.425)	64			
ANSURES	453	3.59 (0)	21.795 (5.111)	28			
C.T.L XR	294	3.59 (0)	44.898 (15.332)	19			
BETAFORM	293	1.975 (0.421)	39.779 (9.512)	42			
MEFORIN	287	1.954 (0.427)	25.802 (9.924)	85			X
Glucomin X.R.	228	3.59 (0)	48.537 (11.837)	18			
METFORMIN(EAYUNG)	220	2.292 (0.427)	29.086 (12.907)	77			
Metformin hydrochloride	198	3.59 (0)	50.655 (0)	16			
Extended-release							
Metformin hydrochloride	32	3.59 (0)	15.75 (0.463)	8	UNITED STATES		
Extended-release							
METFORMIN(C.H.)	136	2.209 (0.445)	29.204 (13.259)	56			
ANTIGLUCO	124	2.056 (0.427)	33.762 (13.055)	46			
PANFORMIN	51	1.805 (0.141)	20.801 (10.849)	23			X
Total	107,241	2.411 (0.622)	27.262 (8.965)	120			

Note: *B* marks brand-name drug. *O* marks the outsourced drug.

the drugs were available during a certain period of time and they were priced differently with different markups, I considered these drugs to be different drugs. Besides, there are two versions of metformin hydrochloride extended-release; one is locally produced while the other is an imported drug from the United States. The mean price and markup reported in Table 1 were averaged over months. The reported price is the regulated price; the acquisition price is not reported but can be derived by subtracting the regulated price of a drug by its markup percentage. Table 1 also labels the drugs that were imported and the drugs whose pharmaceutical providers were listed in the Taiwanese stock market.

Table 1 shows that the brand-name drug Glucophage was prescribed the most often and had the second highest average price in the sample. Glucophage is also among the drugs that existed throughout the whole sampling period. The average

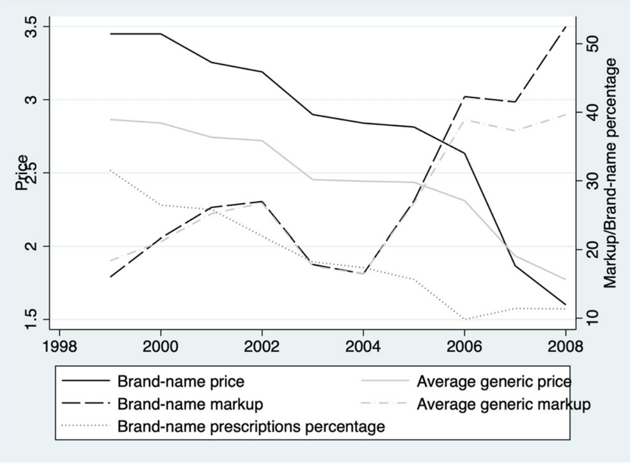

FIGURE 1 Trends of price, markup and prescription percentage by brand-name and generic drugs.

price of these drugs ranges from NT$1.5 to NT$3.59 per DDD; the average price of all the drugs is about NT$2.4. The average markup percentage from prescribing these drugs is about 27.26%. The drugs with the highest markup percentage in the sample, C.T.L. XR and Glucomin X.R., have markups that are about half of their regulated prices. Most of the mean markups reported in Table 1 exceed the regulated 16%; this shows that some providers were still likely to acquire markups higher than 16% for a drug while the regulated price was subject to the average level. As the price would be brought down later after the price adjustments, the providers could switch to another drug with similar therapeutic effects but a higher markup.

Most of the drugs included in the sample were available before the launch of the NHI in 1995, including the brand-name drug. Thus, physicians should have known these drugs during the sampling period. Because these drugs were covered by the NHI, the pharmaceutical providers of these drugs negotiated with the NHI administration and provided the drugs to all the medical providers, who also contracted with the NHI. The availability of these drugs under this single payer system should not be a concern; it is the physicians' decision to choose which drugs to prescribe and dispense. As the price of these drugs are also cheap, I assume that the providers would had access to all of the drugs when making their choices.

Figure 1 shows the trends of average price, markup and prescription percentage by brand-name and generic drugs. The price trends of both types of drugs decreased during the sampling period, as did the brand-name prescription percentage. The decreasing price indicates that the markup had been high. As shown in Figure 1, the trends of markup percentage have been increasing since 2004. Medical providers likely received similar amounts of markup as the percentage of markup went up while the price went down. As the brand-name prescriptions kept decreasing after 2004, providers might have switched from brand-name drugs to the generic drugs with higher profit margins.[13]

Table 2 reports the summary statistics. The average price of the OHAs prescribed is about NT$2.7, where more than a quarter of this price is providers' average profit margin. The prescribed OHAs had been covered by the NHIA for more than 5 years on average, and more than one-third of them were imported. The physician owners prescribed slightly more than half of the prescriptions. These owners were most likely the owners of clinics, as the clinics account for nearly half of the observations. About 88% of the prescriptions were prescribed by physician dispensers. Table 2 also shows that most of the hospitals and clinics are privately owned. The accreditation level is 1 for academic medical centers, 2 for metropolitan hospitals, 3 for regional hospitals and 4 for clinics. The hospitals are different in their size measured by the number of beds, where academic medical centers are the largest. Hospitals with higher accreditation levels have fewer observations in the sample. Patients' copayments are about 16% of their total expenses. The severeness of their diabetes was measured using the Diabetes Complications Severity Index (DCSI, Young et al., 2008). The sample includes only patients who received metformin treatments, so most of them were in an early stage of diabetes and thus the average severity is relatively low.

The average Herfindahl-Hirschman Index (HHI) reported in Table 2 indicates the markets in Taiwan were quite concentrated. Figure 2 averages among the observed prescriptions on their price, markup and brand-name prescription percentage by market. Comparing to the HHI of a given NHI branch, Figure 2 reveals that in the more competitive markets, such as the NHI branches 3 and 4, medical providers prescribed more of the drugs with lower markup percentages or higher prices, likely the brand-name drugs. The providers in the markets that are more concentrated, such as the NHI branches 1 and 2, prescribed more of the drugs with higher markups and lower prices, likely the generic drugs. While these are just anecdotal evidence, Figure 2 reveals that medical providers' prescription choices are related to the competitiveness in their local markets. The average HHI of the medical providers who prescribed a given drug is listed in the Appendix Table A1. The table also reveals the other average characteristics related to prescriptions for each drug. For example, Bicanol was prescribed mostly by the physician owners. Some drugs were never prescribed by the public medical providers during the sample period, especially the drugs that entered the formulary later such as Panformin.

TABLE 2 Summary statistics.

Variables	Mean	SD
Drug		
Markup	25.779	10.831
Price	2.709	0.559
Outsource	0.011	0.103
Vintage	61.818	35.365
Import	0.369	0.483
Stock	0.162	0.368
Physician		
Owner	0.539	0.498
Dispenser	0.882	0.322
Experience[a]	11.158	12.529
Age	44.587	8.598
Facility		
HHI	0.423	0.284
Public	0.162	0.368
Age	8.113	9.457
Academic medical center	0.149	0.356
Metropolitan hospital	0.176	0.380
Regional hospital	0.209	0.407
Clinic	0.466	0.499
Patient		
Percentage NHI coverage	84.153	11.493
Diabetes complications severity index	0.183	0.494
Age	55.550	12.820
Sex (Male = 1)	0.552	0.497
Market		
Population density (per km^2)	7556.412	8283.204
Sex ratio (M/F*100)	102.874	5.798
Number of households (in thousands)	50.866	38.149
Household income (in millions)	0.797	0.190
Total observations	107,241	

[a]A doctor's experience is measured in years between her certification year and the sampling year.

4 | EMPIRICAL MODEL

This section proposes a discrete choice model that accounts for the agency relationship between patients and medical providers. A decision maker in the model chooses among available drugs to treat patients and is defined by the characteristics of physicians, patients, and hospitals or clinics. These characteristics were seldom considered in the previous literature likely because of data availability. Traditional demand analysis that focuses on product characteristics does not include these dimensions.

Consider a medical provider choosing an OHA j for a patient in each quarter t, where $j = 0, \ldots, J_t$ and $t = 1, \ldots, T$. $j = 0$ indicates the outside option, the brand-name drug Glucophage. The number of available choices J_t varies with t. Consider provider and patient to be paired as i in a visit, $i = 1, \ldots, I$. Define $U_{ijt} = U_{ijt}(\Pi_{ijt}, z_{ijt})$ as the pair i's utility gained from an OHA j prescription in quarter t. Π_{ijt} is the financial benefits received by a provider from prescribing j at time t as a pair i. z_{ijt} includes the other factors that could affect the provider's prescription choices, such as the characteristics of physicians, clinics and hospitals, and patients. The medical provider then makes her prescription choices by maximizing the utility. Doctors acting as perfect agents for patients would not consider their own financial benefits when making a prescription choice. Thus, the agency problem is defined as the effect of Π_{ijt} on the provider's prescription choices.[14]

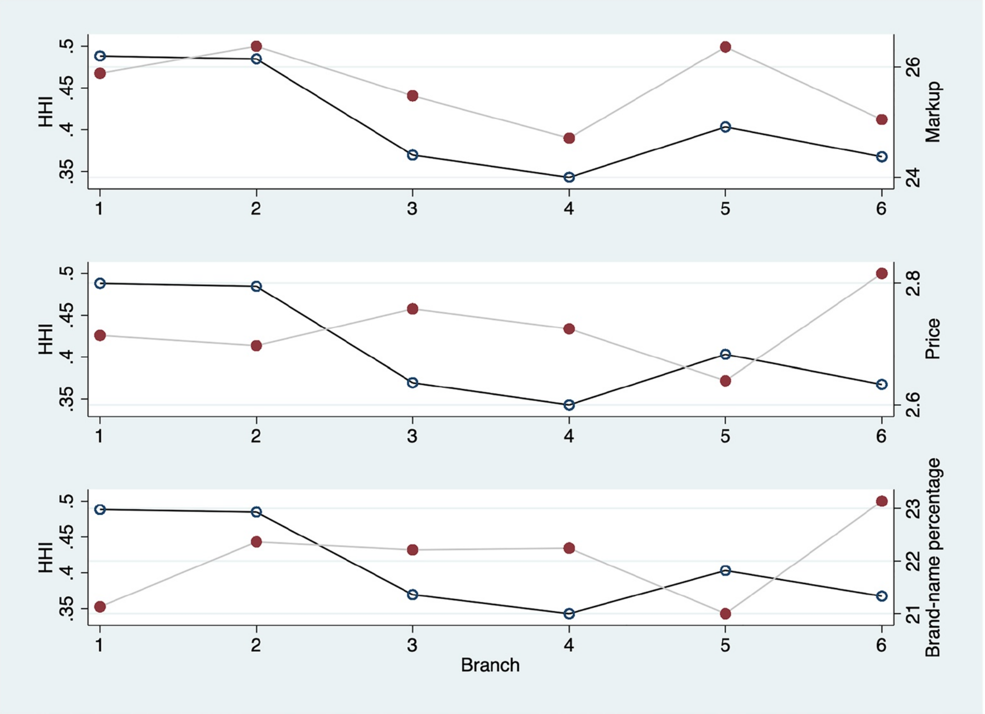

FIGURE 2 Market Competition and the Prescription Price, Markup and Brand-name Drug Percentage. Averages of markup, price and brand-name prescriptions were taken over each branch. In particular, there are six administrative regions under the NHI governance, and these are considered the markets for the medical providers. The HHI of each branch is depicted by the black line in each figure, while the gray line depicts markup, price and brand-name prescription rate in each branch from top figure to bottom figure, respectively. The figures reveal that in the more competitive markets, such as the NHI branches 3 and 4, medical providers prescribed more of the drugs with lower markup percentages or higher prices, likely the brand-name drugs. The providers in the markets that are more concentrated, such as the NHI branches 1 and 2, prescribed more of the drugs with higher markups and lower prices, likely the generic drugs.

Ideally, an exact measure of Π_{ijt} could provide the information on each provider-patient pair i's financial benefits from prescribing drug j at time t. However, only drug-specific information was able to be retrieved, including the price and average markup of a drug as discussed in Section 2.2. This information only varied by drug and time, and it is denoted as π_{jt}. Instead of the level of markup, the markup percentage of drug price is considered since markup percentage is the target of pharmaceutical regulation in Taiwan. Since Π_{ijt} varies among provider-patient pairs, it is thus modeled to vary with medical providers by interacting π_{jt} with provider characteristics. In particular, U_{ijt} was expanded by assuming linearity with an additive error term ε_{ijt} as follows:

$$U_{ijt}(\pi, x, z) = \sum_k \pi_{jkt}\alpha_{ikt} + \sum_n x_{jnt}\beta_{int} + \xi_{jt} + \varepsilon_{ijt}. \tag{3}$$

$\sum_k \pi_{jkt}\alpha_{ikt}$ is a linear combination of empirical proxies that account for the provider's financial benefits Π_{ijt}, where k indicates the kth observed characteristic of the financial profits from a prescription j at time t. It varies among providers by interacting the drug-specific financial benefits π_{jt} with the provider characteristics α_{it}. This allows the model to distinguish providers' heterogeneous preferences regarding π_{jt}. Other drug characteristics are included in x'_{jnt}. Dummy variables D_{jt} are also included in the regression such that $x_{jt} = \left(D_{jt}, x'_{jt}\right)$, where D_{jt} equals 1 if drug j was prescribed in a visit t. x_{jt} was interacted with other provider characteristics β_{it} that were not considered in α_{it}, such as doctor's age or hospital's operation years. ξ_{jt} represents the product characteristics that are unobserved in the data. As stressed by BLP, ξ_{jt} represents the unobserved drug characteristics that likely correlate with price, such as drug quality, and could bias the estimation. ε_{ijt} then absorbs any unobserved, time-variant factors remaining after controlling for the observed drug characteristics π_{jt} and x_{jt} and the provider characteristics α_{it} and β_{it}.

Following MicroBLP and Dunn (2012), I modeled α_{it} and β_{it} as random coefficients with the observed provider's characteristics $\left(z^1_{it}, z^2_{it}\right)$ and indexes γ and ω such that

$$\alpha_{ikt} = \bar{\alpha}_{kt} + \sum_{\gamma} z^1_{i\gamma t}\alpha_{k\gamma t} \tag{4}$$

$$\beta_{int} = \bar{\beta}_{nt} + \sum_{\omega} z^2_{i\omega t}\beta_{n\omega t}. \tag{5}$$

The $z^1_{i\gamma t}$'s are the variables proxied for an individual provider's responsiveness to financial incentives from prescription drugs, π_{jt}. Physician owners and physician dispensers are assumed to be more responsive than the other physicians. Mitchell (2005), Baker et al. (2016) and Howard et al. (2017) also considered the physician-owners' prescription choices to be more profit-oriented than those of the employed physicians. Iizuka (2012) found that doctors in Japan who both prescribe and dispense drugs are more responsive to profit margins from prescription drugs. I also allowed medical institution characteristics, including public ownership, competition in the local market, and accreditation level, to be related with the profit margin from prescriptions. Specifically, public providers are considered to be less responsive to their financial incentives. Providers in more competitive markets are likely more responsive to the patients' demands. For example, Bennett et al. (2015) found that the providers located in more competitive markets prescribed more antibiotics per patients' requests. Accordingly, these providers are less likely to prescribe some drugs even when their profit margins are high. At last, providers' accreditation level controls for the different incentive structures embedded in the hospitals and clinics in Taiwan as discussed in Section 2.

A doctor's experience is also included in $z^1_{i\gamma t}$. Doctors' responses to π_{jt} are thus allowed to vary with the above characteristics in the estimation via Equations (3) and (4). It is worthwhile to mention that $\alpha_{k\gamma t}$ in Equation (4) contain the coefficient estimates of the interaction terms $\pi_{jkt} z^1_{i\gamma t}$, while α_{ikt} in Equation (3) contain random coefficients and is a function of provider's characteristic $z^1_{i\gamma t}$ as shown in Equation (4).

$z^2_{i\omega t}$ consists of the characteristics other than those included in $z^1_{i\gamma t}$, including the ages of physicians, patients, and hospitals and clinics. Patients' percentage of insurance coverage in each visit,契 severeness of their diabetes and sex are also included in $z^2_{i\omega t}$. Market characteristics including population density, sex ratio, number of households and average income were also included. These variables were interacted with the dummy variables D_{jt}, so they would enter the analysis only with the drug that was prescribed in a visit. $\bar{\alpha}_{kt}$ and $\bar{\beta}_{nt}$ then represent the common preferences of the providers to product characteristics π_{jkt} and x_{jnt} in Equation (3), respectively, while $\alpha_{k\gamma t}$ and $\beta_{n\omega t}$ capture the heterogeneous effects of individual characteristics in response to the drug characteristics in Equation (3).

Substituting Equations (4) and (5) into Equation (3), the provider's utility function becomes

$$U_{ijt} = \delta_{jt} + \sum_{k\gamma} \pi_{jkt} z^1_{i\gamma t}\alpha_{k\gamma t} + \sum_{n\omega} D_{jt} z^2_{i\omega t}\beta_{n\omega t} + \varepsilon_{ijt} \tag{6}$$

$$\delta_{jt} = \sum_{k} \pi_{jkt}\bar{\alpha}_{kt} + \sum_{n} x_{jnt}\bar{\beta}_{nt} + \xi_{jt}, \tag{7}$$

where δ_{jt} is a product-specific constant term that is common among providers. The control variables $z^2_{i\omega t}$ entered the utility via the interactions with D_{jt} and only appear when $D_{jt} = 1$. $z^2_{i\omega t}$ was not interacted with the product characteristics x'_{jkt} to reduce the computational burden.

Without distribution assumptions on ξ_{jt}, Equation (6) can be estimated using a standard logit model. Assuming ε_{ijt} follows a type I extreme value distribution, the probability of a provider-patient pair i choosing an OHA j in a visit t is the logit form conditional on $\left(z^1_{it}, z^2_{it}\right)$, where $Pr_{it}\left(j|z^1_{it}, z^2_{it}, \pi_{jt}, x_{jt}; \alpha, \beta, \delta\right) =$

$$\frac{\exp\left(\delta_{jt} + \sum_{k\gamma} \pi_{jkt} z^1_{i\gamma t}\alpha_{k\gamma t} + \sum_{n\omega} D_{jt} z^2_{i\omega t}\beta_{n\omega t}\right)}{1 + \sum_{q=1}^{J_t} \exp\left(\delta_{qt} + \sum_{k\gamma} \pi_{qkt} z^1_{i\gamma t}\alpha_{k\gamma t} + \sum_{n\omega} D_q z^2_{i\omega t}\beta_{n\omega t}\right)}. \tag{8}$$

Treatments with brand-name drugs prescribed were considered as the base group, where the medical provider's utility was set at zero. Equation (8) can be estimated by a conditional logit model to identify (α, β, δ). In the empirical analysis, I first estimated Equation (8) using the full sample for the effect of physician agency on prescription choices, $\alpha_{k\gamma t}$. I then estimated Equation (8) again using the samples from each quarter to obtain estimates on δ_{jt} for each drug j in each quarter t.

The estimates of mean utility δ_{jt} from Equation (8) are to be used as the dependent variable in the second stage estimation involving Equation (7), where $\left(\bar{\alpha}_{kt}, \bar{\beta}_{nt}\right)$ can be identified using standard least squares estimation. However, potential endogeneity in π_{jkt} could bias the coefficient estimates. While the pharmaceutical price was exogenously regulated by the NHIA, profit margin varies among medical providers based on their bargaining power against pharmaceutical providers. The bargaining power is related to provider characteristics such as the accreditation level, which also relates to patients' demand for a drug. Liu et al. (2012) considered the regulated price in Taiwan to be endogenously determined because the unobserved acquisition price and demand of a drug are both related to provider characteristics. This paper separates the effect of acquisition price from the regulated price by controlling for the average markup of each drug. Pharmaceutical price is therefore considered as exogenously determined, while the profit margin is endogenous in the empirical model. Because the individual markup from each drug remains unobserved, the measurement error on profit margin also creates endogeneity.

To address the endogeneity concern, TSLS is applied to estimate Equation (7). Three IVs are used in the estimation: First, a dummy variable that equals one when a price adjustment was implemented is used as an IV. The seven price adjustments exogenously changed the price of drugs and thus the profit margin of providers, but patients' demand of a drug was not affected. Second, I used the yearly number of pharmaceutical providers supplying an OHA in the NHI formulary as another IV. As the competition among the pharmaceutical providers in the OHA market is likely to affect the profit margin acquired by the medical providers, patients' demand of drugs with metformin is less related with the number of competitors in the OHA market. Third, I used the total number of OHAs in the NHI formulary provided by a pharmaceutical provider in a year as another IV. Iizuka (2007) mentioned that multi-product firms would set the prices of all their products by maximizing joint profits. But this pricing strategy is not related to patients' demand for a drug. Iizuka (2007) also argued that the development of a new drug is lengthy and the timing of arrival is hard to predict, which implies that the manufacturing decision is not likely to respond to providers' instantaneous demand change. While this paper focuses on generic drugs, a significant amount of time is required for approval to enter the NHI formulary. It also takes time for physicians and patients to learn and accept the new drug. Thus, pharmaceutical providers might be less likely to respond to the physicians' and patients' demand by producing a new drug. Accordingly, I considered the three IVs to have a direct effect on the profit margin π_{jkt} but not on the mean utility δ_{jt} in Equation (7).

With the estimates of Equations (7) and (8), the price elasticity of the *jth* OHA for each physician-patient pair *i* in the *t* visit, ϵ_{ijt} can be calculated as follows:

$$\epsilon_{ijt} = \frac{\partial Pr_{it}(j)}{\partial p_{jt}} \frac{p_{jt}}{Pr_{it}(j)} = \frac{\partial U_{ijt}}{\partial p_{jt}} p_{jt}(1 - Pr_{it}(j)). \tag{9}$$

The aggregate elasticities ϵ_j for the *jth* OHA are calculated by taking averages from the individual results in each quarter.

5 | EMPIRICAL RESULTS

This section first reports the results using the full sample to estimate the conditional logit model Equation (8). Total observations were augmented because each prescription choice was considered as a result from the choice set with more than 30 drugs; the observations would be augmented by roughly 30 times the original sample size in the estimation. The same model was then applied using quarterly subsamples to estimate δ_{jt} for each drug *j* in each quarter *t*, which is then used for the TSLS estimation on Equation (7). When doing the estimation using quarterly subsamples, the drugs ranking in the bottom six based on number of prescriptions in a quarter were not used in the estimation. More choices were dropped in some quarters to achieve convergence, but there are at least 20 choices available in each quarter for estimation. Besides, considering that physician-patient pair could appear multiple times in the data, fixed effects by pairs were controlled in the conditional logit model. As most of the doctors have multiple patients in the sample, the variances of coefficient estimates were clustered by doctor.

Table 3 reports the estimates of $\alpha_{k\gamma t}$ for the interaction terms $\sum_{k\gamma} \pi_{jkt} z^1_{i\gamma t}$ in Equation (6). The results show that the physician dispensers are more likely to prescribe drugs with higher prices. These drugs likely have lower profit margins as previously discussed, and the estimates indicate the physician dispensers cared more about the price of a drug than its markup percentage. These results came mostly from the physicians in clinics, as the estimates are statistically insignificant when using only the hospital sample. Physician owners were found to be more likely to prescribe the drugs with higher markup percentages, especially the owners of hospitals. These estimates reveal significant agency effects from the physicians who are more responsive to the financial incentives, as a perfect agent for patients would not consider these factors when prescribing drugs. Table 3 also reveals that medical providers are more responsive to the markup percentages from prescription drugs than their prices, as the estimates on price are mostly statistically insignificant.

Table 3 also shows the other agency effects, where the markup percentage of a drug would affect prescription choices of the providers with certain attributes. Private hospitals and clinics are more likely than the public ones to prescribe drugs with higher markups. The estimate shows that private-owned hospitals and clinics are more responsive to profits than the public ones. Medical providers located in a less competitive market are more likely to prescribe drugs with higher margins. Because patients had fewer alternatives in less competitive markets, the providers in these markets could prescribe more of their preferred drugs

TABLE 3 Mixed logit estimates for the agency effects.

Variables/Sample	Full	Hospitals	Clinics
Interacted with markup			
Dispenser	−0.007*	−0.003	−0.011**
	(0.004)	(0.008)	(0.005)
Owner	0.012*	0.016**	0.005
	(0.007)	(0.008)	(0.007)
Public	−0.047***	−0.020***	−0.064***
	(0.006)	(0.006)	(0.007)
HHI	0.032***	0.027***	0.039***
	(0.007)	(0.011)	(0.008)
Accreditation level[a]	0.008**	0.018***	
	(0.003)	(0.005)	
Experience	0.000	0.001***	−0.000
	(0.000)	(0.000)	(0.000)
Interacted with price			
Dispenser	0.235***	−0.003	0.323***
	(0.061)	(0.123)	(0.065)
Owner	0.056	0.126	0.032
	(0.076)	(0.116)	(0.096)
Public	0.091	−0.104	0.052
	(0.069)	(0.075)	(0.087)
HHI	−0.123	0.127	−0.151
	(0.115)	(0.208)	(0.117)
Accreditation level[a]	0.020	−0.010	
	(0.039)	(0.056)	
Experience	0.002	0.001	0.003*
	(0.001)	(0.004)	(0.002)
Total observations:	3,538,953	1,773,262	1,600,640

[a]The accreditation level is 1 for academic medical centers, 2 for metropolitan hospitals, 3 for regional hospitals and 4 for clinics. Other control variables include the doctor's age, the operation years of the hospital or clinic, the patient's share of expenses, severeness of diabetes, and gender. Market characteristics are also controlled for, including population density, sex ratio, number of households and average income. Markup is not instrumented. Standard deviations were adjusted for clusters in physicians.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

that would otherwise deter patients. Tang (2021) found that medical providers who faced less competition in Taiwan prescribed more inappropriate antibiotics than other medical providers did. In addition, smaller providers like clinics or regional hospitals are more responsive to profit margins from prescriptions. Experienced physicians are more likely than other physicians to prescribe the drugs with higher markup percentages; this is especially the case of physicians in hospitals.[15]

In addition to the provider heterogeneity, the results when including interaction terms between markup and price and patient characteristics are reported in Appendix Table A2. The inclusion only slightly changes the estimates of the providers' characteristics reported in Table 3 without affecting their statistical significance. The results show that the patients with a higher percentage of copayment are more likely to receive expensive drugs with lower markup percentages. The statistically significant estimates reveal the providers' agency problem, where the providers might not consider the patients' share of medical expenses when prescribing drugs. Tang and Wu (2020) also found this agency problem among hospital physicians. While their paper focuses on physicians' double agency problem that considers both patients' and payer's utility in their decision, the current paper focuses on the providers' heterogeneity in their agency problem. Besides, the estimate is small and only significant when using the full sample. Thus, the subsequent analyses use the estimates from Table 3.

The conditional logit model expressed in Equation (8) was applied to the quarterly subsample to obtain δ_{jt}'s. They are then used as the dependent variable in Equation (7) and estimated by TSLS. Table 4 reports the results from the first and second

TABLE 4 Estimation results from two stage least squares.

	Full sample		Hospital sample		Clinic sample	
Variables	**First stage**	**Second stage**	**First stage**	**Second stage**	**First stage**	**Second stage**
Dependent variable	**Markup**	**δ**	**Markup**	**δ**	**Markup**	**δ**
Markup		2.463*		1139.651		2.717*
		(1.290)		−1446.524)		(1.548)
Price	7.390***	−1.666	8.553***	−11000	6.942**	5.924
	(1.249)	(23.258)	(1.732)	(13000)	(1.401)	(30.220)
Outsource	−2.888***	19.078*	1.254	−1900	−2.922**	21.762*
	(0.818)	(11.392)	(1.134)	(2701.463)	(0.851)	(13.057)
Vintage	0.307***	−1.824	0.218**	−245.525	0.262***	−1.916
	(0.068)	(1.153)	(0.099)	(323.795)	(0.073)	(1.302)
Vintage squared	−0.001**	0.009	−0.000	0.052	−0.001	0.009
	(0.000)	(0.007)	(0.001)	(0.880)	(0.001)	(0.007)
Import	−1.583*	32.732	−2.817**	3278.991	−1.446	35.348
	(0.863)	(29.292)	(1.098)	(4316.525)	(0.877)	(31.829)
Stock	0.153	−2.535	0.184	337.364	0.058	−2.451
	(0.859)	(3.829)	(0.971)	(1127.180)	(0.882)	(4.093)
Instrumental variables:						
Number of products	−0.395**	Yes	−0.144	Yes	−0.410**	Yes
	(0.175)		(0.210)		(0.182)	
Number of suppliers	−0.333	Yes	−1.086	Yes	−0.369	Yes
	(0.564)		(0.689)		(0.592)	
Price adjustment	2.557***	Yes	0.686	Yes	2.262**	Yes
	(0.945)		(1.136)		(0.947)	
First stage F-statistic	5.072***		1.708		4.340***	
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Total observations	589		368		551	

Note: Standard deviations were robust and adjusted for clusters in the oral hypoglycemic agents.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

stage regressions, using both the full sample and the hospital and clinic subsamples. Results from the first stage regressions verify the validity of the IVs; both the number of products and the number of competitors of a pharmaceutical provider are found to reduce the markup percentage of a drug. Price adjustments were positively related to profit margin because the adjustments were made to reduce high markups from prescriptions. Coefficient estimates of the number of suppliers are not statistically significant, however, and the same is true for the other IVs when using the hospital subsample. The F-statistics from the first-stage regressions suggest that the IVs are likely to be weak when using the hospital sample. This does not affect the following elasticity estimates and counterfactual analysis because they are based on the full-sample estimates.

Table 4 reports the positive relationship between markup percentage and demand. The estimates are statistically significant using the full sample and clinic sample, indicating the demand of clinics is more responsive to the markup percentage of a drug than is the demand of hospitals. The estimates using the hospital sample are much larger than the ones using the clinic sample because the estimated common demand of the drugs, δ_{jt} in Equation (7), is much larger for the hospital physicians than the clinic physicians. In particular, the average delta estimate for hospital physicians per drug is 200.36 with a standard deviation of 2176.11; the corresponding statistics for clinic physicians are 3.14 and 94.32. The estimates show that the common demand for each drug is much higher for hospital physicians than clinic physicians. This is expected because more than half of the patients in the sample visited hospitals, especially the patients with serious diabetes.[16]

Table 4 also shows that drug price is negatively related with demand when using the full sample and hospital sample. It became positive when using the clinic sample, but the estimate is statistically insignificant. Outsourced drugs are found to be preferred by physicians, especially the ones working in clinics. The demand of drugs was not significantly related with the other drug characteristics. In addition, the results using the ordinary least squares method are also reported in Appendix Table A3. The results using the full sample show that, without considering endogeneity, the signs of estimates of price and markup are different and statistically insignificant. The results reduce the concern of collinearity between price and markup, where the price is a positive predictor of markup as shown in the first stage.

The estimates of price elasticities are reported in Table 5. The estimates are averages from ϵ_{ijt} by j and t, which are also reported in Table 5 as the number of prescriptions and number of quarters, respectively. Some drugs appeared in only one quarter and thus do not have variation in their estimates.

The elasticities are high for most of the drugs, indicating physicians are quite sensitive to the pharmaceutical price adjustments. The average elasticity is −2.34. All the estimates are negative except the ones for Betaform; its demand is inelastic. The elasticity estimate of the imported version of metformin hydrochloride extended-release is quite small. The estimates reported in this paper are larger than the average estimates for patients in the literature, which is about −0.2 to −0.6 for copayments (Goldman et al., 2007). The results indicate that the providers' price elasticity is larger than the patients', particularly after controlling for individual heterogeneity across physicians, patients, and hospitals and clinics. The variation of the elasticity estimates across the diabetes drugs also indicates the importance of accounting for provider heterogeneity in the estimation.

6 | COUNTERFACTUAL ANALYSIS

This section reports estimates on the total effect of physician agency measured by welfare change using counterfactual analysis. I used the formula suggested by Train (2009) to calculate the welfare change as follows:

$$\Delta E(CS)_{it} = \frac{1}{-\bar{\alpha}_{price}}\left[\ln\left(\sum_{j=0}^{J_t} e^{U_{it\_after}}\right) - \ln\left(\sum_{j=0}^{J_t} e^{U_{it\_before}}\right)\right]. \tag{10}$$

$\bar{\alpha}_{price}$ is the coefficient estimate of price in Equation (7), which is considered as the marginal utility of money and assumed to be fixed. $-\bar{\alpha}_{price}$ is the marginal utility of income. Equation (10) was calculated for each observation it following the steps below:

1. Calculate $\sum_{j=1}^{n} e^{U_{it\_before}}$ using the estimates from Equation (6) and the original value of the variables. This estimate was also used in calculating elasticity.
2. Calculate $\sum_{j=1}^{n} e^{U_{it\_after}}$ by replacing some of the variables under the following five counterfactual scenarios:
   (a) Set the markup percentage of each OHA as zero. The price of each OHA is thus the average of reported procurement price $\overline{P_{jt}^{p}}$ calculated in Equation (2) for each OHA j at time t. U_{it_after} is then calculated after replacing the original values of price and markup percentage in Equation (6).
   (b) Removing physician dispensing services by letting the physician dispenser dummy be zero for the whole sample.
   (c) Removing physician ownership by letting the physician owner dummy be zero for the whole sample.
   (d) Removing private ownership by letting the public ownership dummy be one for the whole sample.
   (e) Repeating 2a, 2b, 2c and 2d altogether.

These scenarios center on the physicians who are more responsive to financial incentives: dispensers, owners and the ones working in private hospitals and clinics. Removing profit margin from prescribing a drug shows the effect of pharmaceutical pricing on the physician-patient pairs' change of utility. As the estimates obtained from the first stage are likely not causal, the results from counterfactual analysis should be interpreted with this in mind.

Table 6 reports the counterfactual estimates. Under each scenario, I reported the average utility change by a dose. Average ΔCS by claim is the ΔCS by dose multiplied by the number of doses prescribed in each claim. Total ΔCS is the sum of all the ΔCS of each claim in the sample. To make the estimates comparable to the actual numbers, I found the total number of outpatient claims reimbursed for diabetes patients during 1999 to 2008 is 67,606,873.[17] In my original sample, the metformin prescriptions account for about 37.73% of the total prescribed OHAs. I thus considered the total number of claims with metformin to be 25,690,612 in the population. The claims used in the counterfactual analysis is thus about 0.415% of the population claims. I then estimated the total change of consumer surplus for the entire population by dividing total ΔCS by 0.415%. The resulting estimates is comparable with the total expenses reimbursed for diabetes outpatient services during 1999 to 2008, NT$91,545,392,944 or US$2.786 billion. This value was calculated separately for clinics and hospitals, discounting each year's total reimbursed points by the point value of a sector in that year. Again, suppose that the metformin prescriptions account for

TABLE 5 Price elasticity estimates for the oral hypoglycemic agents.

	Price elasticity estimates		Number of	Number of
Product	**Mean**	**SD**	**Quarters**	**Prescriptions**
ANSURES	−2.579	4.406	9	10,765
ANTIGLUCO	−1.802	0.808	4	1455
BENTOMIN	−3.913	6.143	31	93,784
BETAFORM	0.176	4.365	10	5705
BICANOL	−3.945	8.785	14	8410
C.T.L XR	−5.534	2.431	7	7580
DIAFORMIN	−3.177	6.698	37	128,014
GLIBUDON	−2.686	6.097	39	208,922
GLIBUDON[A]	−1.663	0.862	5	31,153
GLUBIN	−2.444	6.573	36	58,104
GLUCOFIT ER	−3.400	0	1	319
GLUCOFIT F.C.	−1.398	6.792	38	56,754
GLUCOMINE	−2.513	6.725	40	146,582
Glucomin X.R.	−4.517	2.306	5	5821
LIAL	−0.984	6.143	37	28,215
LODITON	−0.522	5.622	33	99,300
LODITON[A]	−1.942	0.916	5	9221
MEFORIN	−2.333	5.685	7	1874
MEGLUMINE	−2.662	8.569	33	36,655
METFORMIN(KINGDOM)	−1.190	6.011	35	74,306
METFORMIN(KINGDOM)[A]	−1.996	0.940	5	7536
METFORMIN	−2.749	7.123	38	108,933
METFORMIN(LITA)	−4.385	6.468	11	5021
METFORMIN(C.H.)	−2.039	0.863	4	1156
METFORMIN(EAYUNG)	−0.302	4.578	5	1373
METFORMIN(S.F.)	−4.237	7.825	18	15,227
METO	−0.713	0	1	232
Metformin hydrochloride Extended-release	−2.006	1.176	6	5123
Metformin hydrochloride[I] Extended-release	−0.000	0.000	2	480
UFORMIN	−2.168	3.631	24	62,674
UFORMIN[A]	−1.233	0.864	4	5489
VOLV	−2.497	7.577	40	90,274
VOLV[A]	−1.810	0.719	5	15,516
Total	−2.340	6.307	589	208,922

about 37.73% of the total expenses, NT$34,536,619,088 or US$1.051 billion. The percentage of consumer surplus change relative to this expense is then reported in Table 6. Estimates using US$ are also reported using the average exchange rate during 1999 to 2008, US$1 for NT$32.85426.

Table 6 shows that, by removing markup from all the drugs in the sample, a physician-patient pair would increase their utility by about NT$5.5 per claim. This adds up to about an increase of US$4.28 million in the population, which accounts for about 0.408% of the outpatient expenses on metformin prescriptions during 1999 to 2008. The estimate reveals that patients would gain from removing markup even when it would hurt physicians. It is because the agency effects estimated in the upper half of Table 3 would be completely removed when setting the markup percentage at zero. The agency effect with price is also lower when reducing the regulated price to the average acquisition price.

TABLE 6 Counterfactual estimates.

Consumer Surplus Change	No Markup	No Dispenser	No Owners	No Private	No Dispenser No owners No private	Triple Equivalence
Average ΔCS per dose	0.119	−0.279	−0.167	−0.467	−0.789	0.464
	(1.539)	(0.245)	(0.237)	(0.411)	(0.531)	(1.291)
Average ΔCS per claim	5.519	−12.014	−6.969	−20.628	−34.321	18.237
(multiple doses)	(76.691)	(14.382)	(12.406)	(25.119)	(34.560)	(55.980)
Total ΔCS per dose	12,556	−29,570	−17,687	−49,387	−83,548	49,092
Total ΔCS per claim	584,211	−1,271,712	−737,637	−2,183,533	−3,632,939	1,930,396
Population estimate in NT$	140,769,696	−306,427,616	−177,738,656	−526,137,184	−875,381,504	465,141,972
Population estimate in US$	4,284,671	−9,326,876	−5,409,912	−16,014,276	−26,644,384	14,157,737
Percentage total expenses	0.408	−0.887	−0.515	−1.523	−2.535	1.347

When removing physicians' characteristics that are related to physician agency, Table 6 shows that physicians' loss in utility would outweigh the patients' gain. Table 6 shows that if physician dispensers, owners, and private ownership were removed in the sample, the consumer surplus per claim would be reduced by NT$12, NT$7 and NT$21, respectively. Removing private ownership would account for more than 1.523% of the total outpatient expense on metformin, a loss of US$16.01 million. If all these characteristics were removed simultaneously, Table 6 reports the loss of consumer surplus change is about 2.535% of the outpatient expense on metformin, a loss of US$26.64 million. These negative welfare estimates do not suggest removing physician agency is bad for society, but it is certainly not preferred by medical providers. The estimates reveal that the aggregate impact of physician agency from prescriptions could be large, as the estimates reported here are confined to only 33 drugs with metformin.

While it would be impossible to restrict physician ownership and private ownership, the counterfactual estimates suggest potential benefits for regulating physicians' dispensing services. Policy tools that aim to reduce the markup of prescription drugs could also use the above framework to estimate potential impact. For example, in July 2014 the Taiwanese government launched a "triple equivalence" policy regulating that drugs with the same ingredients and quality be reimbursed at the same price. It aimed to reduce the price of brand-name drugs that had been listed in the NHI formulary for more than 15 years, and nearly 9000 drugs were affected.[18] The implementation of this policy caused a lot of concerns in Taiwan; for example, the representatives of pharmaceutical companies were worried that some brand-name drugs would be removed from the Taiwanese market because of fierce price competition with generic replacements. To analyze the likely effect of this policy, I set the price of all the OHAs to be the minimum price in each quarter. The associated markup percentage with the minimum price was then considered as the markup for all the drugs in that quarter. If there are multiple markup percentages found with the same minimum price, I picked the larger one as the markup percentage for all the drugs. Table 6 shows this policy would increase consumer surplus by about NT$18 per dose for an average physician-patient pair. Total consumer surplus change is estimated at US$14.16 million, which is 1.347% of the total outpatient expense on metformin. The policy effect is larger than the effect from removing markup from each prescription drug because the price was also lowered. This shows that policies aiming to regulate pharmaceutical price and markup can significantly increase the aggregate welfare of patients and providers under insurance coverage. The effect is likely larger than the effect from regulating physician agency directly, for example, by restricting physicians' dispensing services.

7 | CONCLUSION

As medical providers are allowed to both prescribe and dispense drugs in Taiwan, they have strong incentives to put their own interests with those of patients' and the health insurance system when making prescription choices. Since Taiwan implemented a universal health care system funded by all citizens, the agency problem in this market implies that patients are likely paying for the providers' profits by receiving sub-optimal medical services.

Using a sample from a population-based database in Taiwan, this paper estimates this agency effect by considering provider characteristics in pharmaceutical demand analysis using a discrete choice model with the information on medical provider characteristics and their average profit margin from each prescription. Empirical results reveal statistically significant marginal effects of physician agency and a sizable welfare effect of this problem. Empirical estimates show that physician owners, privately-owned medical providers, small medical providers and the medical providers facing less competition are more likely to prescribe drugs with higher profit margins. Physician dispensers are found to be more likely to prescribe the more expensive drugs. Controlling for the endogenous profit margin, the estimation reveals a downward sloping pharmaceutical demand curve that is positively related with the profit margin of each drug.

Counterfactual analysis shows that the policies restricting pharmaceutical price and profit margin are welfare enhancing for patients. Regulating potential sources of physician agency such as physicians' dispensing services would reduce medical providers' profit, but it is not as effective as the policy restricting pharmaceutical price and profit margin.

Taiwanese health authorities have been bothered by the medical providers' profit margin from prescription drugs since the beginning of the implementation of the universal health care system, coined by Cheng (2003) as the "drug price black hole" problem. This is the first study to quantify the potential size of this problem in Taiwan. Because universal health care has been gradually adopted around the world, the findings of this paper are suggestive for other countries that are preparing to implement universal healthcare and the countries allowing for pharmaceutical promotions such as detailing and advertising. This paper provides limited evidence on the impact of physician agency because it is based on a restricted number of drugs due to computational capacity. A lack of data on the true profit margin of each medical provider also prevents the estimates from being more precise. Future research without these limitations may be able to find better estimates of the impact of physician agency in Taiwan and around the world.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data Sources: 1. Restricted access: This research is based in part on data from the National Health Insurance Research Database provided by the National Health Insurance Administration, Ministry of Health and Welfare and managed by National Health Research Institutes, Taiwan. The author is not permitted to share the data, but the data that support the findings of this study are available from the Data Center, National Health Insurance Administration, Ministry of Health and Welfare. Restrictions apply to the availability of these data, and applications are required to access the data. Details on the application and related procedure for the access to the data are available at https://www.nhi.gov.tw/Content_List.aspx?%20n=B8D0E95BA43F696B&topn=-787128DAD5F71B1A%202. Public access: The drug information used in this study is public available at https://www.nhi.gov.tw/QueryN_New/QueryN/Query1.

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ENDNOTES

[1] For more details, see the report by Sun (2016) of *The China Post*.

[2] Whoriskey and Keating of The Washington Post (2013) also reported that U.S. physicians profit from more-costly treatments when alternatives are equally effective. This costs Medicare a billion dollars or more of extra payments annually. Mitchell and Korenstein (2020) of The STAT News summarized related news and research on how payments and gifts from pharmaceutical companies affected physicians' prescribing in the United States.

[3] McGuire (2000), Chandra et al. (2012), Ho and Pakes (2014) and Clemens and Gottlieb (2014) provide an overview of the relevant literature on physician agency and how the financial incentives direct medical providers' choices in many aspects of the health care industry.

[4] McGuire (2000) and Chandra et al. (2014) surveyed the related theoretical and empirical studies on physician agency and physician-induced demand under this setting. Theoretical papers studying physicians' incentives focus on the asymmetric information between providers and patients and the uncertainty of providers' treatments. Most of the research focuses on how insurance payers can alleviate these concerns through contractual means. For example, see Blomqvist (1991), Taylor (1995) and Pflum (2015).

[5] Counterfactual analysis provides the estimates on the size of physician agency from these two sources, which has been rarely estimated in the existing literature. Iizuka (2007) is an exception that provides an estimate of potential vertical separation by restricting physicians to dispense drugs in Japan. This paper extends his analysis by also examining the physician ownership and public ownership. I also applied the estimates to simulate the policy effect of a policy implemented in Taiwan. Dunn (2012) also conducted a counterfactual analysis with focus on consumer welfare change.

[6] Since 2014, the World Health Organization and the World Bank Group have made universal health care coverage their priority to improve global health. For related reports and news coverage, see http://universalhealthcoverageday.org/news/, http://www.who.int/universal_health_coverage/en/ and a recent report by the World Health Organization (2015).

[7] Pricing rules regarding brand-name and generic drugs are different and conditional on their bio-equivalent test results. Since 1997, the NHIA has used a uniform pricing policy that follows a "generic grouping rule" that prices the pharmaceuticals by their patent status, bioavailability/bioequivalence (BA/BE) availability, and the median price in other countries. Liu et al. (2012) and Hsu and Lu (2015) provide more details on the pricing of drugs listed in the NHIA formulary.

[8] Hsu et al. (2014) studied the effect of a price adjustment in 2006 on medical providers' prescriptions of oral anti-diabetic products. They separated the oral hypoglycemic agents (OHAs) by whether their prices were targeted in this price adjustment and whether the OHAs were locally produced. They found that medical providers reduced prescriptions of the targeted OHAs and internationally produced OHAs after the price adjustment, while the prescriptions of non-targeted OHAs that were produced locally were increased after the adjustment.

[9] Another major difference between Iizuka (2012) and this paper is the type of drugs included in the analysis. This study focuses on diabetes drugs while Iizuka (2012) studied drugs across different diseases. Focusing on a single disease avoids the concerns that treatments among different diseases are not comparable, but Iizuka's (2012) adoption of drugs for different diseases shows the results are sufficiently general to cover various treatments.

[10] For detailed information on how the NHIRD located those patients with diabetes and how they sampled the data, please see the NHIRD website http://nhird.nhri.org.tw/en/Data_Subsets.html#S3.

[11] http://www.nhi.gov.tw/Query/query1.aspx?menu=18&menu_id=703, in Chinese.

[12] The population data are available at the website of the Ministry of Interior, Taiwan, https://www.ris.gov.tw/app/portal/346. Household income data were obtained from the Ministry of Finance, Taiwan, https://www.fia.gov.tw/multiplehtml/43.

[13] The downward trend of markup during 2002 to 2004 is likely a result of the implementation of global budgeting on hospitals and related policy adoptions. Tang (2022) documented a health reform in 2004 in Taiwan, the Hospital Excellence Initiatives (HEI). The policy allows hospitals in Taiwan to negotiate individual budgets under the global budget system, which was implemented in 2002 and resulted in some hospital bankruptcies. Tang (2022) showed that the HEI significantly reduced the outpatient services of the participant hospitals, which implies hospitals increased their service volumes when competing for the global budget. Accordingly, when some hospitals operated under their own budgets in 2004, they might have negotiated with pharmaceutical firms differently than previously under the global budget. This potential policy effect was controlled for in the regressions by including year fixed effects.

[14] While Uijt is obtained after each treatment, the decisions on the pharmaceutical purchases and inventory management were likely made in the beginning of each month. Although the providers may not know the type of patients that would pay visits in a month, they are assumed to have an expectation on the potential types of patients based on their previous experience when purchasing the drugs. A dynamic model with medical providers learning based on their experience from each period would release the assumption; see Ching (2010b, 2010a).

[15] The number of coefficient estimates of βnωt in Equation (6) is large. Thus, the estimates are not reported, but they are available upon request.

[16] The observation counts in the subsamples do not sum up to the number of observations in the full sample because the drugs dropped in each quarterly subsample are different when using the full sample and the subsamples. As mentioned in the first paragraph of Section 5, when doing the estimation using quarterly samples, the drugs ranking in the bottom six based on number of prescriptions in a quarter were not used in the estimation. Thus, the hospital subsample and the clinic subsample could have different drugs dropped in each quarter.

[17] The statistics were obtained from the website of the Ministry of Health and Welfare, https://dep.mohw.gov.tw/DOS/np-1918-113.html (in Chinese).

[18] For the announcement of the NHIA (in Chinese), please refer to http://www.nhi.gov.tw/epaperN/ItemDetail.aspx?DataID=3617&IsWebData=0&ItemTypeID=3&PapersID=318&PicID=

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

TABLE A1 Summary statistics by the prescribed oral hypoglycemic agents.

	Drug	Physician			Hospital			
Product	Released	Owner	Experience	Age	HHI	Public	Size	Age
GLUCOPHAGE	0.893 (0.308)	0.344 (0.475)	9.265 (10.383)	43.384 (9.159)	0.410 (0.254)	0.348 (0.476)	2.525 (1.192)	5.946 (5.382)
DIAFORMIN	0.936 (0.245)	0.416 (0.493)	9.581 (12.989)	42.021 (7.437)	0.545 (0.323)	0.282 (0.450)	2.605 (1.267)	6.329 (4.716)
METFORMIN	0.905 (0.293)	0.575 (0.494)	10.371 (13.021)	43.899 (8.071)	0.360 (0.234)	0.224 (0.417)	3.260 (0.854)	13.764 (24.081)
Metformin hydrochloride	0.938 (0.246)	0.063 (0.246)	11.438 (4.111)	43.094 (6.635)	0.743 (0.107)	0 (0)	1.188 (0.738)	14.656 (1.234)
Extended-release								
GLUCOMINE	0.889 (0.314)	0.677 (0.468)	12.021 (14.157)	45.567 (8.804)	0.345 (0.250)	0.180 (0.384)	3.371 (0.792)	7.190 (6.469)
MEGLUMINE	0.903 (0.296)	0.807 (0.394)	12.917 (15.022)	43.889 (6.394)	0.276 (0.157)	0.002 (0.040)	3.764 (0.459)	7.249 (5.245)
METFORMIN(EAYUNG)	0.959 (0.199)	0.614 (0.488)	8.395 (4.896)	43.195 (9.283)	0.397 (0.288)	0.391 (0.489)	3.345 (0.799)	7.036 (4.361)
METFORMIN(LITA)	0.861 (0.347)	0.961 (0.193)	13.891 (18.913)	49.279 (10.139)	0.231 (0.143)	0.004 (0.065)	3.936 (0.246)	6.981 (5.802)
BICANOL	0.932 (0.253)	0.946 (0.227)	11.934 (15.453)	47.624 (10.189)	0.371 (0.273)	0.053 (0.224)	3.884 (0.320)	6.349 (5.653)

TABLE A1 (Continued)

Product	Drug	Physician			Hospital			
	Released	Owner	Experience	Age	HHI	Public	Size	Age
UFORMIN	0.903 (0.297)	0.213 (0.410)	9.431 (7.112)	42.566 (6.949)	0.610 (0.267)	0.037 (0.188)	2.062 (1.070)	10.429 (6.959)
UFORMIN^A	0.962 (0.192)	0.038 (0.192)	10.761 (6.189)	42.751 (7.609)	0.538 (0.221)	0 (0)	2.502 (0.573)	25.761 (4.168)
METFORMIN(C.H.)	0.919 (0.274)	0.993 (0.086)	11.544 (5.207)	49.301 (6.527)	0.388 (0.249)	0 (0)	3.706 (0.457)	5.875 (3.662)
METFORMIN(S.F.)	0.921 (0.270)	0.864 (0.342)	13.195 (18.689)	44.726 (8.984)	0.270 (0.216)	0.035 (0.183)	3.814 (0.389)	4.553 (4.483)
METFORMIN(KINGDOM)	0.885 (0.319)	0.703 (0.457)	14.517 (15.430)	47.952 (9.401)	0.355 (0.252)	0.017 (0.131)	3.450 (0.631)	8.817 (6.448)
METFORMIN(KINGDOM)^A	0.888 (0.316)	0.364 (0.482)	14.455 (11.500)	47.857 (7.529)	0.470 (0.285)	0.014 (0.118)	3.192 (0.395)	14.070 (7.141)
BETAFORM	0.717 (0.451)	0.846 (0.361)	14.198 (9.221)	48.468 (5.729)	0.502 (0.190)	0 (0)	3.587 (0.493)	11.109 (4.251)
VOLV	0.807 (0.395)	0.773 (0.419)	13.168 (16.173)	46.433 (8.836)	0.386 (0.282)	0.030 (0.170)	3.533 (0.794)	7.537 (6.032)
VOLV^A	0.897 (0.305)	0.361 (0.481)	13.764 (13.906)	45.908 (9.381)	0.731 (0.248)	0.118 (0.323)	2.282 (1.190)	10.527 (4.585)
LIAL	0.838 (0.368)	0.919 (0.273)	15.596 (18.174)	47.125 (8.094)	0.281 (0.210)	0.023 (0.151)	3.820 (0.416)	6.811 (5.869)
BENTOMIN	0.959 (0.197)	0.303 (0.460)	9.238 (8.935)	42.178 (7.001)	0.569 (0.342)	0.033 (0.178)	2.323 (1.165)	8.290 (5.631)
GLUCOFIT	0.769 (0.422)	0.801 (0.399)	13.590 (14.272)	46.550 (8.609)	0.373 (0.256)	0.044 (0.206)	3.655 (0.495)	7.725 (5.417)
MEFORIN	0.916 (0.277)	0.944 (0.230)	23.345 (25.483)	52.746 (8.943)	0.297 (0.176)	0 (0)	3.969 (0.175)	8.265 (6.246)
GLUBIN	0.886 (0.318)	0.575 (0.494)	11.165 (13.647)	43.370 (7.843)	0.310 (0.200)	0.130 (0.336)	3.202 (0.880)	8.497 (5.128)
AANTIGLUCO	0.895 (0.308)	0.597 (0.493)	24.032 (25.809)	45.427 (6.133)	0.397 (0.259)	0.347 (0.478)	3.548 (0.500)	7.379 (4.151)
GLIBUDON	0.897 (0.304)	0.544 (0.498)	10.951 (8.831)	45.397 (8.417)	0.452 (0.291)	0.103 (0.304)	2.941 (1.095)	9.143 (10.784)
GLIBUDON^A	0.885 (0.319)	0.156 (0.363)	11.675 (6.462)	45.195 (8.299)	0.737 (0.268)	0.028 (0.166)	2.277 (0.981)	11.946 (7.574)
PANFORMIN	0.706 (0.460)	0.824 (0.385)	15.902 (21.580)	42.392 (7.561)	0.183 (0.120)	0 (0)	3.647 (0.483)	10.647 (10.237)
LODITON	0.746 (0.435)	0.862 (0.345)	13.326 (12.599)	47.300 (8.068)	0.364 (0.274)	0.027 (0.161)	3.725 (0.578)	8.423 (9.794)
LODITON^A	0.753 (0.432)	0.514 (0.501)	11.787 (7.240)	44.778 (7.935)	0.492 (0.232)	0.034 (0.182)	3.153 (1.099)	14.332 (6.581)
ANSURES	0.726 (0.446)	0.631 (0.483)	12.605 (8.725)	45.640 (7.754)	0.469 (0.221)	0.104 (0.305)	3.711 (0.464)	9.638 (4.470)
C.T.L XR	0.918 (0.274)	0.051 (0.220)	14.024 (17.793)	41.037 (6.194)	0.755 (0.176)	0.922 (0.269)	1.316 (0.829)	10.357 (3.532)
Glucomin X.R.	0.798 (0.402)	0.785 (0.412)	14.864 (6.393)	50.053 (7.569)	0.529 (0.323)	0.070 (0.256)	3.728 (0.575)	11.746 (5.886)
Metformin hydrochloride	0.955 (0.209)	0.152 (0.359)	11.237 (7.406)	42.313 (7.422)	0.747 (0.145)	0.020 (0.141)	1.596 (1.051)	16.101 (5.736)

(Continues)

TABLE A1 (Continued)

	Drug	Physician			Hospital			
Product	Released	Owner	Experience	Age	HHI	Public	Size	Age
Extended-Release[I]								
GLUCOPHAGE	84.312	0.202	55.542	0.565	9770.101	101.598	59.331	0.848
	(11.741)	(0.504)	(13.126)	(0.496)	(8892.442)	(5.908)	(39.536)	(0.203)
DIAFORMIN	84.530	0.219	56.431	0.541	4218.153	105.828	36.346	0.764
	(10.230)	(0.549)	(12.538)	(0.498)	(5375.737)	(5.269)	(30.677)	(0.159)
METFORMIN	85.460	0.213	56.058	0.566	6166.971	104.593	38.438	0.729
	(8.085)	(0.527)	(12.781)	(0.496)	(8859.646)	(6.034)	(36.301)	(0.153)
Metformin hydrochloride	78.718	0.063	50.719	0.625	4516.484	96.079	96.101	1.198
	(15.540)	(0.246)	(7.830)	(0.492)	(505.507)	(1.423)	(10.284)	(0.086)
Extended-release								
GLUCOMINE	85.114	0.175	56.009	0.555	7003.576	104.064	39.300	0.737
	(9.819)	(0.486)	(12.656)	(0.497)	(8529.446)	(6.208)	(32.148)	(0.155)
MEGLUMINE	85.565	0.146	55.301	0.539	5632.87	103.752	48.621	0.752
	(7.809)	(0.404)	(12.291)	(0.499)	(7025.274)	(5.047)	(28.544)	(0.158)
METFORMIN(EAYUNG)	84.763	0.109	53.518	0.577	6808.7	103.284	46.571	0.773
	(11.185)	(0.402)	(13.301)	(0.495)	(6922.277)	(4.206)	(37.014)	(0.147)
METFORMIN(LITA)	85.126	0.075	54.425	0.472	8780.541	102.329	55.909	0.791
	(6.466)	(0.329)	(12.219)	(0.500)	(8214.115)	(4.738)	(43.277)	(0.119)
BICANOL	85.203	0.092	57.268	0.528	6948.945	107.418	37.913	0.703
	(8.497)	(0.370)	(11.956)	(0.500)	(9780.572)	(6.514)	(35.710)	(0.135)
UFORMIN	81.082	0.176	54.086	0.548	10629.84	98.988	64.926	0.929
	(16.683)	(0.488)	(13.324)	(0.498)	(7854.698)	(5.473)	(36.455)	(0.234)
UFORMIN[A]	86.721	0.316	56.033	0.493	12788.83	96.817	44.821	0.799
	(13.063)	(0.609)	(10.617)	(0.501)	(7545.131)	(4.315)	(24.136)	(0.044)
METFORMIN(C.H.)	86.227	0.022	56.199	0.426	10655.13	102.447	73.684	0.814
	(7.006)	(0.147)	(12.080)	(0.496)	(7275.843)	(8.883)	(42.432)	(0.172)
METFORMIN(S.F.)	85.369	0.122	55.543	0.559	6259.732	104.772	50.275	0.717
	(7.083)	(0.376)	(12.267)	(0.497)	(7552.181)	(6.968)	(36.645)	(0.123)
METFORMIN(KINGDOM)	85.269	0.186	55.585	0.527	6834.292	102.665	49.353	0.760
	(8.775)	(0.512)	(12.979)	(0.499)	(7293.826)	(5.003)	(35.214)	(0.175)
METFORMIN(KINGDOM)[A]	86.161	0.150	53.685	0.612	10491.52	98.441	61.797	1.015
	(7.950)	(0.468)	(14.033)	(0.488)	(8222.157)	(4.496)	(29.848)	(0.378)
BETAFORM	87.195	0.150	57.734	0.713	3330.634	103.676	29.853	0.727
	(7.975)	(0.494)	(13.339)	(0.453)	(4761.637)	(4.059)	(19.290)	(0.107)
VOLV	83.951	0.103	55.355	0.523	6672.916	103.872	54.251	0.749
	(11.151)	(0.390)	(13.397)	(0.500)	(7546.784)	(5.598)	(41.777)	(0.140)
VOLV[A]	79.296	0.143	54.097	0.509	10369	98.605	61.161	0.984
	(20.745)	(0.438)	(12.189)	(0.500)	(7488.853)	(8.490)	(42.213)	(0.262)
LIAL	85.077	0.239	54.649	0.564	10793.44	101.553	61.152	0.787
	(7.325)	(0.549)	(12.438)	(0.496)	(8647.28)	(5.090)	(39.934)	(0.150)
BENTOMIN	81.778	0.218	54.335	0.578	5670.128	103.346	53.901	0.816
	(11.414)	(0.587)	(12.785)	(0.494)	(6805.311)	(4.549)	(40.723)	(0.163)
GLUCOFIT	86.269	0.148	55.421	0.530	8223.876	102.265	57.901	0.771
	(7.527)	(0.411)	(12.765)	(0.499)	(9208.237)	(4.775)	(38.738)	(0.153)
MEFORIN	84.890	0.021	58.014	0.603	8285.354	101.494	58.237	0.851
	(7.057)	(0.166)	(13.308)	(0.490)	(6611.913)	(4.775)	(37.442)	(0.204)
GLUBIN	83.935	0.117	54.799	0.565	5769.535	102.793	54.369	0.763
	(12.362)	(0.388)	(12.912)	(0.496)	(7246.762)	(4.004)	(33.539)	(0.136)

TABLE A1 (Continued)

	Drug	Physician			Hospital			
Product	**Released**	**Owner**	**Experience**	**Age**	**HHI**	**Public**	**Size**	**Age**
ANTIGLUCO	90.610 (9.069)	0.048 (0.281)	59.863 (12.309)	0.565 (0.498)	7678.586 (7818.267)	102.942 (5.040)	53.595 (47.157)	0.760 (0.103)
GLIBUDON	83.021 (13.789)	0.192 (0.500)	55.742 (12.729)	0.543 (0.498)	7539.439 (8132.136)	102.490 (5.273)	50.037 (36.430)	0.824 (0.211)
GLIBUDON[A]	79.443 (20.709)	0.143 (0.459)	53.222 (12.134)	0.569 (0.495)	8884.613 (8278.613)	98.835 (6.098)	55.626 (34.198)	0.942 (0.322)
PANFORMIN	84.607 (3.350)	0.137 (0.348)	52.804 (13.425)	0.804 (0.401)	11165.49 (8467.787)	99.943 (2.206)	75.538 (8.931)	0.794 (0.121)
LODITON	84.716 (9.411)	0.164 (0.450)	56.125 (12.315)	0.546 (0.498)	7903.809 (9137.065)	103.568 (5.638)	47.981 (42.853)	0.741 (0.142)
LODITON[A]	84.318 (14.141)	0.335 (0.771)	56.219 (11.155)	0.514 (0.501)	8778.042 (7609.84)	101.063 (5.204)	69.420 (50.375)	0.790 (0.115)
ANSURES	88.845 (7.607)	0.137 (0.386)	56.777 (11.751)	0.574 (0.495)	6804.114 (6629.255)	101.203 (4.321)	59.985 (37.722)	0.795 (0.136)
C.T.L XR	75.717 (24.330)	0.340 (0.535)	53.929 (11.553)	0.609 (0.489)	8754.306 (3727.711)	98.070 (3.505)	67.365 (22.098)	0.960 (0.159)
Glucomin X.R.	87.034 (9.301)	0.123 (0.329)	56.197 (11.726)	0.570 (0.496)	3857.14 (3439.669)	102.342 (5.314)	43.417 (31.425)	0.797 (0.126)
Metformin hydrochloride Extended-Release[I]	76.557 (23.702)	0.116 (0.351)	53.232 (9.637)	0.616 (0.488)	4795.085 (3689.523)	96.897 (4.438)	76.440 (34.969)	1.095 (0.245)

Note: *A* marks aluminum packaging. *I* marks the imported drug.

TABLE A2 Mixed logit estimates for the agency effects with patient characteristics.

Variables/Sample	**Full**	**Hospitals**	**Clinics**
Interacted with markup			
Dispenser	−0.007*	−0.003	−0.011**
	(0.004)	(0.008)	(0.005)
Owner	0.012*	0.017**	0.005
	(0.007)	(0.008)	(0.007)
Public	−0.046***	−0.020***	−0.064***
	(0.006)	(0.006)	(0.007)
HHI	0.032***	0.027**	0.004***
	(0.007)	(0.011)	(0.008)
Accreditation level[a]	0.008**	0.018***	
	(0.003)	(0.005)	
Experience	0.000	0.001***	−0.000
	(0.000)	(0.000)	(0.000)
Percentage NHI coverage	−0.000***	−0.000***	−0.000
	(0.000)	(0.000)	(0.000)
Diabetes complications severity index	0.001	0.001	0.005*
	(0.002)	(0.002)	(0.003)
Age	−0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)
Sex (Male = 1)	−0.001	−0.001	0.001
	(0.001)	(0.002)	(0.002)

(Continues)

TABLE A2 (Continued)

Variables/Sample	Full	Hospitals	Clinics
Interacted with price			
Dispenser	0.233***	−0.010	0.323***
	(0.061)	(0.122)	(0.065)
Owner	0.057	0.125	0.034
	(0.076)	(0.116)	(0.095)
Public	0.090	−0.104	0.053
	(0.069)	(0.075)	(0.088)
HHI	−0.122	0.128	−0.154
	(0.115)	(0.209)	(0.117)
Accreditation level[a]	0.019	−0.011	
	(0.039)	(0.055)	
Experience	0.002	0.001	0.003*
	(0.001)	(0.004)	(0.002)
Percentage NHI coverage	0.002*	−0.000	−0.002
	(0.001)	(0.001)	(0.002)
Diabetes complications severity index	0.017	0.022	0.005
	(0.003)	(0.032)	(0.042)
Age	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
Sex (Male = 1)	0.012	0.006	−0.012
	0.018	(0.023)	(0.026)
Total observations:	3,538,953	1,773,262	1,600,640

[a]The accreditation level is 1 for academic medical centers, 2 for metropolitan hospitals, 3 for regional hospitals and 4 for clinics. Other control variables include the doctor's age, the operation years of the hospital or clinic, the patient's share of expenses, severeness of diabetes, and gender. Market characteristics are also controlled for, including population density, sex ratio, number of households and average income. Markup is not instrumented. Standard deviations were adjusted for clusters in physicians.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

TABLE A3 Ordinary Least Squares Estimates (Dependent Variable: δ).

Variables/Sample	Full	Hospital	Clinic
Markup	−0.968	−27.783**	−1.084
	(1.072)	(12.946)	(1.187)
Price	25.174	−606.877*	34.151
	(28.999)	(332.963)	(37.634)
Outsource	12.353	29.187	13.725
	(8.754)	(284.410)	(9.707)
Vintage	−0.791	3.962	−0.87
	(0.745)	(13.311)	(0.837)
Vintage squared	0.006	−0.129	0.006
	(0.006)	(0.107)	(0.006)
Import	27.334	15.100	29.417
	(27.282)	(108.273)	(29.138)
Stock	−2.715	568.289*	−2.778
	(3.215)	(340.456)	(3.277)
Year fixed effect	Yes	Yes	Yes
Total observations	589	368	551

Standard deviations were robust and adjusted for clusters in the oral hypoglycemic agents.

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.