Competing Doctors, Antibiotic Use, and Antibiotic Resistance in Taiwan*

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Abstract

Antibiotics are a cornerstone of modern medicine, but antibiotic resistance increasingly threatens to erode their effectiveness. The emergence of drug-resistant pathogens is a negative externality associated with antibiotic use. Many patients, who do not internalize this social cost, prefer physicians who casually prescribe antibiotics. If offering these drugs increases demand, physicians may respond to competition by prescribing antibiotics more frequently. This paper examines the effect of competition in outpatient health care markets on antibiotic use in Taiwan. In a large, nationally representative dataset of outpatient visits, an increase in competition of one standard deviation raises antibiotic use by up to 2.4 percent. Patient and physician fixed effects and the interaction with a policy to limit antibiotic use point to an effect of competition on behavior, rather than a spurious correlation. The paper then calibrates the relationship between antibiotic use and resistance to estimate the effect of competition on this outcome. An increase in competition of one standard deviation elevates resistance by up to 11.5 percent, leading to $1.36 billion in additional costs, or 35 percent of Taiwan’s antibiotics budget over 60 years.

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1 Introduction

With the first commercial production of penicillin in 1943, antibiotics revolutionized medicine by offering effective and inexpensive treatment for bacterial infections. Antibiotics are effective against pneumonia, tuberculosis, gonorrhea, urinary tract infections, and many other illnesses with varying degrees of severity. By inhibiting bacterial metabolism and reproduction, a typical seven-day course of antibiotics can eliminate an infection with fewer risks or side effects than other, more invasive procedures. These drugs have saved millions of lives and contributed to the expansion of live expectancy in the US from 62.9 years in 1940 to 68.2 years a decade later (Arias 2006). However, ubiquitous antibiotic use has fostered the development of drug-resistant pathogens. Bacteria, which reproduce in a matter of hours and days, evolve rapidly in response to selective pressure. Consuming an antibiotic encourages bacteria to mutate in ways that circumvent the drug’s antibacterial mechanism. Antibiotic use also helps to propagate existing resistant strains by eliminating susceptible strains that would otherwise compete for nutrients.

Drug resistance threatens public health throughout the world by increasing the cost and challenge of treating bacterial infections. As they have aged, many first-line antibiotics have lost clinical effectiveness through high rates of resistance. Erythromycin, which came into use in 1960, is a common treatment for pneumonia, meningitis, and other *S. pneumoniae* infections. However, resistance of *S. pneumoniae* to erythromycin now reaches 28.3 percent in the United States, 33.3 percent in Mexico, 71.5 percent in Japan, and 72.4 percent in Hong Kong (McGeer and Low 2003). Patients with resistant infections face a greater risk of morbidity and mortality and require more elaborate treatments, which impose a sizeable burden on the health care system. Lautenbach et al. (2001) find that drug resistance delays the delivery of effective treatment by 2.5 days, leading to longer and more expensive hospital stays. By one estimate, the US spends $4-7 billion per year to treat patients with drug-resistant infections (ASM 1995). In a recent headline-grabbing study, Klevens et al. (2007) report that deaths due to methicillin-resistant *S. aureus* (MRSA) now outnumber deaths due to AIDS, Parkinson’s Disease, emphysema, and homicide in the US.

The present-day costs of drug resistance, while not trivial, are small compared to the potential costs of infection control if antibiotics were to lose effectiveness. According to a fact sheet from the ReAct Group (2007), an NGO, “Antibiotics are the cornerstone of modern medicine and have revolutionized medical care during the last half of the previous century. Thus, in order to calculate the full economic burden of antibiotic resistance, we have to consider the burden of not having antibiotics at all, which at the extreme will probably collapse the entire medical system.” The likelihood of this contingency depends
upon whether pharmaceutical companies are able to invent new antibiotics to replace drugs with high resistance. However, Spellberg et al. (2004) report that research into drugs for obesity and heart disease is crowding out the development of new antibiotics.

The development of drug resistance is a negative externality associated with antibiotic use. Doctors and patients, who seek to overcome a particular infection, do not incorporate the incremental effect of consuming antibiotics on community-wide resistance. Elbasha (2003) models this externality and calculates that the social cost of excessive consumption of amoxycillin (a common first-line antibiotic) in the US is $225 million per year. A welfare accounting of antibiotic use must also recognize that these drugs have a positive externality through reduced disease transmission. Laxminarayan and Brown (2001) use an epidemiological SIS framework to model the tradeoff between these externalities. Since the benefit of antibiotic use accrues in the short run but drug resistance develops over many years, myopic policymakers (such as term-limited elected officials) have an incentive to promote antibiotic use through policy. The inconsistency between the typical duration of patents and the time horizon of antibiotic resistance also distorts the incentives of pharmaceutical companies. Facing future competition from generics, drug companies may seek to maximize use of antibiotics that are under patent, irrespective of the impact on future drug resistance (Horowitz and Moehring 2004). Incentive misalignments for various decision makers help to explain the rise in antibiotic resistance.

Both patients and doctors have an incentive to overuse antibiotics, but patients, who frequently view antibiotics as potent alternatives to aspirin or cold medicine, are likely to prefer these drugs even more than doctors. Physicians learn about drug resistance in medical school and confront ethical constraints on casual antibiotic use. Patients, on the other hand, face an information disadvantage relative to physicians and seek visual cues of the physician’s quality. Like the physician’s effort or attentiveness, the willingness to prescribe antibiotics may serve as a quality signal for patients (Das and Sohnesen 2006). Findings from focus groups of physicians describe the tension between patients who are eager to receive antibiotics and physicians who are uncomfortable dispensing them. Butler et al. (1998) quote one physician’s sentiment: “It does make me feel uncomfortable. I do feel as though I’ve been slightly used. Sometimes slightly abused as well.” Bauchner et al. (1999) confirm the pervasiveness of this phenomenon: 96 percent of US-based pediatricians in their survey receive inappropriate requests for antibiotics, and one third comply with these requests at least occasionally. Many patients have a favorable view of doctors who prescribe antibiotics casually.

Under these conditions, a physician’s demand is increasing in his or her willingness to use antibiotics. Offering antibiotics is a particular example of quality competition, where
“quality” refers to anything that the patient finds valuable about the office visit. Doctors may seek to differentiate themselves by liberally supplying antibiotics, particularly if price regulation prevents them from competing in prices. In this framework, the marginal benefit to a hospital or clinic of supplying antibiotics is decreasing in its market power, which is inversely proportional to the firm’s quality elasticity of demand. With a low elasticity of demand, the firm receives relatively little additional business from an incremental quality increase. In contrast, marginally increasing quality has a large payoff for a firm with little market power and a high elasticity of demand. Intuitively, a monopolist has a smaller incentive to offer quality because it must also offer this quality level to the inframarginal customers it has already captured. Analogous reasoning applies in a standard model of monopoly, in which the firm sets price above marginal cost for the same reason. This simple theory implies that competition may encourage physicians to prescribe antibiotics more freely.

Several papers in the industrial organization literature have examined the theoretical effect of competition on product quality. In general, firms respond to competition by raising quality as long quality improvements lead to greater demand. Spence (1975) proves this basic result in the context of a price-regulated monopoly by showing that the monopolist supplies an in efficiently low level of quality. Quality is an increasing function of the firm’s elasticity of demand, so that reducing the monopolist’s market power leads to a quality increase. A model in which a monopolist also sets the price is slightly more complicated. Under the assumption that firms set price equal to average cost, raising quality only increases the firm’s demand if the quality elasticity of demand exceeds the price elasticity of demand (Dorfman and Steiner 1954). A firm with a high price elasticity may respond to competition by reducing both price and quality. Incorporating oligopoly into a price-regulated model raises the additional issue that the effect of competition depends on how strongly firms react to quality increases by their competitors. Beil et al. (1995) show that a firm who increases quality may elicit such a strong reaction from its competitors that its demand actually falls; in this case competition does not lead to higher quality. The authors acknowledge, however, that this scenario applies primarily to small and tightly-knit oligopolies and that the effect of competition on quality is clearly positive under other circumstances.

In the health economics literature, quality competition has arisen most prominently in terms of the so-called medical arms race. Robinson and Luft (1985) postulate that hospitals may respond to competition by investing in costly equipment and services that patients and referring physicians prefer. By implication, competition may partially explain rising hospital costs and health care cost in general. Dranove and Satterthwaite (2000,
Section 4.2) summarize the debate and the mixed empirical evidence on this question. Hospitals negotiate with designated purchasers such as HMOs over both price and quality, and these purchasers may exhibit lower quality sensitivity and greater price sensitivity than the consumers they represent. If the price elasticity of demand is larger than the quality elasticity, hospitals will respond to competition by cutting both price and quality. The salience of each type of elasticity depends upon the institutional and regulatory setting. For instance, the UK’s National Health Service contracts with hospitals through many geographically specialized purchasers. Since consumer choice over purchasers is limited, purchasers bargain for cost savings rather than quality. Propper, Burgess and Green (2004) use hospital-specific mortality data to show that hospitals in the UK respond to competition by modestly reducing quality.

This paper examines how competition among physicians affects antibiotic use and antibiotic resistance in Taiwan. Taiwan is a rapidly industrializing economy with technology intensive health care. Due to extensive antibiotic use in the past, antibiotic resistance in Taiwan is higher than either the US or Europe (Lauderdale et al. 2004, McDonald et al. 2004). The country features a publicly-administered national health insurance program that is based on the fee-for-service model, and the government sets the price of health care through the reimbursement rate. In response to escalating antibiotic use in the late 1990s, the government implemented a novel regulatory experiment to reduce antibiotic consumption. The policy, which required physicians to document the bacterial cause of URIs in order to prescribe antibiotics, dramatically reduced antibiotic use and attenuated the effect of competition.

Competitive prescription of antibiotics is a particular hazard in Taiwan for cultural and institutional reasons. Ho (2005, p. 246) comments on the typical doctor-patient interaction:

Physicians frequently spend only 3-5 minutes or so for a single ambulatory patient. Clearly one cannot do a thorough diagnostic workup under such time constraints. One might ask, why do patients in Taiwan put up with five-minute visits with their physician? The answer is that their primary purpose in seeing a doctor is to get a prescription. It is easy to give the patient a prescription in five minutes. This excessive demand for medicines is cultural. In the Chinese conception, every illness requires some sort of medicine. The idea that some diseases do not require medicine is unacceptable.

Taiwanese patients visit outpatient providers a median of 10 times per year. This high frequency reflects the tendency of Taiwanese patients to consult a physician about minor conditions such as sore throats and colds. Physicians, who receive revenue from each visit, may request multiple follow-ups and limit the duration of prescriptions so that patients will return. In addition, Chen et al. (2006) document the pattern of “doctor shopping,”
in which patients consult with several doctors about a condition to ensure a satisfactory response. Many Taiwanese patients expect to receive antibiotics and are uninhibited about seeking them elsewhere if a physician refuses to prescribe.

The data from Taiwan are also particularly strong. Through the Bureau of National Health Insurance (BNHI), the government centrally manages all claims and tracks the health care utilization of the 96 percent of the population who rely on public insurance. Our analysis is based on a panel dataset containing the outpatient visits of a representative sample of patients from 1997 to 2005, which the BNHI makes available to researchers. The data also include a census of health care providers, from which we construct a Hirschman-Herfindahl Index (HHI) of market concentration. In regressions of antibiotic use on market concentration, the dataset allows us to employ patient and physician fixed effects simultaneously. The paper also relies on antibiotic resistance data that are available through a surveillance of around two dozen hospitals across Taiwan to estimate a growth curve of antibiotic resistance.

The paper begins with a simple theoretical framework that illustrates the link between antibiotic use and market concentration. We model firm entry as endogenous and solve for concentration and use in terms of demand and supply parameters in order to highlight the sources of correlation between these variables. After describing the context and the data, the paper presents regressions of antibiotic use on market concentration. The main concern in these regressions is that heterogeneity in demand or supply may generate a spurious correlation. However, the result persists after employing both patient and physicians fixed effects, which control for time-constant heterogeneity. To address the concern about time-varying heterogeneity, we examine the interaction between market concentration and a policy that regulated antibiotic prescriptions. The policy, which took effect in February of 2001, required physicians to justify their antibiotic prescriptions in cases of upper respiratory infection (URI). The enhanced regulation eliminates the effect of competition on antibiotic use, which is consistent with a physician response to competition and is inconsistent with bias from time-varying heterogeneity. Our estimates indicate that a decline in concentration of one standard deviation increases antibiotic use by 2.4 percent under the original regulatory environment.

An extension to the model considers the implications of a de facto limit on prescription, which limits the discretion of physicians treating high-use patients. This theory may explain differences in the strength of the competition effect across the age distribution, and between hospitals and clinics. The final section estimates the cost of competitive antibiotic use by calibrating the link between antibiotic consumption on antibiotic resistance. We find that a 2.4 percent increase in consumption raises resistance by up to 11.5 percent, depending
Upon the drug’s age. Under assumptions about the cost of treating resistant infections, this effect leads to $1.36 billion in additional expenditures, or 35 percent of Taiwan’s antibiotics budget over a 60 year period.

2 Theoretical Framework

In the simple model developed below, competition induces physicians to offer patients additional antibiotics. Since other authors have dealt with competition and product quality more generally (Spence 1975, Beil et al. 1995), this section provides intuition for the present context. We modify a standard Cournot model through the assumption that the government fixes the price of a unit of health care. Within a random utility framework, patients receive monotonically increasing utility from antibiotic consumption. Each firm chooses a level of antibiotic use, which determines its patient volume and profit.

2.1 Model Setup

A local health care market contains a fixed number of patients, normalized to 1, who are indexed by \( i \) and each demand \( \theta > 0 \) units of health care. \( n \) homogeneous firms, indexed by \( j \), serve the market and meet patients’ entire health care demand. Firms compete for patients by offering antibiotics, \( a_j \). Since these patients patronize \( n \) firms, it is important to distinguish between \( a_j \), which is the firm’s choice variable, and \( \tilde{a}_j = na_j \), which is antibiotic use per capita, the outcome of interest. Patient utility is a function of antibiotic use and the match quality with the chosen provider, \( \nu_{ij} \): 

\[
    u(\tilde{a}_j, \nu_{ij}) = \ln(\tilde{a}_j) + \nu_{ij}
\]

Under the assumption that \( \nu_{ij} \) has a Type-II Extreme Value distribution, firm \( j \)'s demand is a function of its antibiotic use relative to other firms: 

\[
    q_j = \frac{\theta \times a_j}{\sum_{k=1}^{n} a_k} \quad (\text{McFadden 1974}).
\]

Firms receive compensation \( p > 0 \) from the government and incur cost \( c \in [0, p) \) for each unit of health care that they provide.

Antibiotic prescriptions are subject to government oversight that is costly for firms. Suppose that the government selectively monitors antibiotic use and imposes cost \( \tau \) for each unit of \( \tilde{a}_j \) that it detects, but that the probability of detection is the inverse of the number of firms in the market. Then the cost of prescription, \( \tau(a_j) = \tau \tilde{a}_j/n = \tau a_j \). Firm \( j \) maximizes the following profit function with respect to \( a_j \):

\[
    \max_{a_j} \pi_j = \theta(p - c) \frac{a_j}{\sum_{k=1}^{n} a_k} - \tau a_j \quad (1)
\]

Differentiating expression (1) with respect to \( a_j \) provides a first order condition that must hold for each firm in equilibrium. Firms, which are homogeneous, choose symmetric levels
of antibiotic use: \( a_j^* = a^* \) for all \( j \). Solving the first order condition and imposing symmetry across firms gives an expression for \( a^* \) as a function of \( n \).

\[
a^* = \frac{\theta(p - c)}{\tau} \times \frac{n - 1}{n^2}
\]  

(2)

Differentiating equation (2) with respect to \( n \) shows that antibiotic use per firm declines in the number of firms for \( n > 2 \). The reason for this result is that as \( n \) rises, each firm receives fewer patients and therefore supplies fewer drugs. However, in an aspect that is parallel to the Cournot Model, the number of firms rises faster than the decline in \( a^* \), and aggregate antibiotic use rises in \( n \).

Normalizing equation (2) by \( n \) provides an expression for equilibrium antibiotic use per capita, \( \tilde{a}^* \). This relationship may be equivalently expressed in terms of the Herfindahl Index, \( H \), which is defined as the sum of squared market shares across all firms in the market. In this model, each firm’s share is \( 1/n \), so \( H = \sum_{k=1}^{n} \frac{1}{n^2} = 1/n \):

\[
\tilde{a}^* = \frac{\theta(p - c)}{\tau} \times (1 - H)
\]  

(3)

This expression illustrates the factors in the model that determine antibiotic use. Antibiotic use is increasing in the demand for care, \( \theta \), and the profit margin, \( p - c \), but is decreasing in the intensity of regulation, \( \tau \). Differentiating equation (3) with respect to \( H \) shows that antibiotic use is decreasing in market concentration.

\[
\frac{\partial \tilde{a}^*}{\partial H} = -\frac{\theta(p - c)}{\tau} < 0
\]  

(4)

Intuitively, an increase in \( H \) raises the market power and reduces the elasticity of demand for the remaining firms. A firm considering whether to increase \( a_j \) receives a smaller benefit from this action when market concentration is high.

Equation (4) illustrates the factors that mediate the effect of competition on antibiotic use. The cost of prescribing antibiotics, \( \tau \), appears in the denominator of the expression, indicating that regulation attenuates the effect of competition on prescription. Since this parameter also appears in the denominator of equation (3), regulation should also directly reduce the level of prescription. In contrast, the demand for health care, \( \theta \), has the opposite effect on both antibiotic use and the role of competition. Greater demand per patient accentuates the firm’s profit motive for attracting the patient with antibiotics. An increase in demand enhances both the level of antibiotic use and the effect of competition on use.
2.2 Endogenous Entry and the Herfindahl Index

The preceding subsection derives the effect of market concentration on antibiotic use under the assumption that market concentration is exogenous. A concern in the empirical section below is that demand or supply heterogeneity may cause a spurious correlation between market concentration and antibiotic use. Here we formally consider the endogeneity of $H$ by modeling the entry decisions of firms. First, it is necessary to amend the setup to the model so that entrants incur fixed cost $\kappa$. Firms first decide whether to enter and then choose $a_j$ to maximize profit conditional upon entry. Equation (2) provides the solution to the second-stage problem. To obtain the equilibrium market concentration, we substitute $a^*$ into equation (1) and solve for $n$ by setting equilibrium profit to zero. Since $H = 1/n$, the equilibrium level of market concentration is the inverse of this solution:

$$H^* = \sqrt{\frac{\kappa}{\theta (p - c)}}$$ (5)

This expression shows how the Herfindahl Index depends upon the parameters of the model. The entry barrier, $\kappa$ and the cost of care, $c$, both positively affect $H$. Market concentration is decreasing in patient demand, $\theta$, and the reimbursement rate, $p$. Under the assumption that the cost of offering antibiotics, $\tau$, does not affect the marginal cost of providing care, this parameter does not affect market concentration.

Equations (3) and (5) depict antibiotic use and market concentration as functions of exogenous parameters and illustrate the potential sources of correlation between these variables. Patient demand, $\theta$, enters the denominator of $H^*$ and the numerator of $\bar{a}^*$, meaning that demand increases antibiotic use and lowers market concentration. Conversely, the cost of care, $c$, reduces antibiotic use and increases market concentration. Heterogeneity in either patient or provider characteristics may induce a negative correlation between the HHI and antibiotic use. These equations also identify the entry barrier, $\kappa$, as a source of exogenous variation in $H$ since this variable affects the Herfindahl Index but not per capita antibiotic use.

The derivations of $\bar{a}^*$ and $H^*$ are based on an assumption of homogeneity across firms. In a more general framework, demand, costs, and entry barriers may vary across firms, generating differences in firm sizes, types, and rates of antibiotic use. Firm heterogeneity complicates the theory in two important ways. First competition may affect antibiotic use by changing the composition of firms in the market. Competition forces the lowest-prescribing firms, who are least profitable, to exit the market. The effect of competition on antibiotic use reflects the selection of firms in addition to an effect on physician behavior. Secondly, firms of different sizes may prescribe antibiotics at different rates for institutional reasons.
that are unrelated to competition. The HHI, which is calculated using squared market shares, overweights the contributions of large firms. Therefore, the correlation between antibiotic use and market concentration may reflect the presence of large firms that happen to behave differently.

2.3 Physician Discretion and Patient Heterogeneity

This extension of the model examines how competition affects prescription when physicians have limited discretion over the antibiotic use of some patients. Physicians treating patients with unambiguous infections have less leeway over whether to prescribe antibiotics. These patients, who would receive antibiotics from any physician, use these drugs intensively but have a low elasticity of demand. If non-discretionary demand is an important determinant of antibiotic use, prescription may be insensitive to competition in settings with high levels of use. To formalize this idea, decompose antibiotic use into a discretionary component, \( \hat{a}_j \) and a non-discretionary component, \( b : \tilde{a}_j = \hat{a}_j + b \). An upper bound, \( \overline{a} \), constrains the level of antibiotic use per capita: \( \tilde{a}_j \in [0, \overline{a}] \). Assume that \( \overline{a} > \theta(p - c)/\tau \), so that this cap does not constrain \( \hat{a}_j \) unless \( b > 0 \). An increase in \( b \), which reduces the difference between \( \tilde{a}_j \) and \( \overline{a} \), limits the firm’s latitude to offer discretionary antibiotics.

Suppose the community consists of two patient types, \( t \in \{m, l\} \), who have “more” and “less” non-discretionary antibiotic use. For each patient type, firms choose \( a_{jt} \) to maximize profit. The firm’s total antibiotic use is the linear combination of its use for each patient type:

\[
a_j = \lambda a_{jt}^m + (1 - \lambda) a_{jt}^l,
\]

where \( \lambda \) is the share of patients of type \( m \). Firms maximize the following profit function:

\[
\max_{a_{jm}^m, a_{jl}^l} \pi = \theta(p - c) \left( \lambda \frac{a_{jm}^m}{\sum_{k=1}^{n} a_{km}^m} + (1 - \lambda) \frac{a_{jl}^l}{\sum_{k=1}^{n} a_{kl}^l} \right) - \tau \left( \lambda a_{jm}^m + (1 - \lambda) a_{jl}^l \right)
\]

Equation (6) indicates that profit is additively separable by patient type, so that firms optimize \( a_{jm}^m \) and \( a_{jl}^l \) independently. To illustrate starkly how non-discretionary use, \( b \), diminishes the role of competition, suppose that \( b^m = \overline{a} \) and \( b^l = 0 \). \( \overline{a} \) does not constrain the treatment of type-\( l \) patients but completely constrains the treatment of type-\( m \) patients. The constraint forces firms to set \( \tilde{a}_j^m \) to zero, which implies that \( \tilde{a}_j^{ms} = \overline{a} \), and split the demand from type-\( m \) patients: \( q_{jm}^m = \theta \lambda/n \). By contrast, firm \( j \)’s demand from type-\( l \) patients is a function of \( a_{jl}^l \): \( q_{jl}^l = \theta(1 - \lambda) a_{jl}^l/\sum_{k=1}^{n} a_{kl}^l \). Following the argument in Section 2.1, \( a_{j*}^l = a^{l*} \), which equals \( a^* \) in equation (2). Because neither \( a^{ms} \) or \( a^{l*} \) is a function of \( \lambda \), antibiotic use by each type is independent of the composition of patient types.

The model’s predictions by patient type now follow trivially. Because \( \overline{a} > a^{l*} \), type-\( m \)
patients consume more antibiotics than type-\(l\) patients. Use by type-\(m\) patients is also invariant to market concentration, while use by type-\(l\) patients decreases in concentration: 
\[
\frac{\partial \tilde{a}^l}{\partial H} = -\frac{\theta(p-c)}{\tau} < 0.
\]
Therefore, underlying heterogeneity in non-discretionary use, \(b\), may induce a negative correlation between levels of use and the responsiveness of use to competition. Providers do not compete for patients with high non-discretionary use by offering antibiotics because antibiotics are an ineffective way to attract these patients.

Heterogeneity across firms in patient composition may explain why firms vary in their responsiveness to competition. Let \(\lambda_j\) be the exogenous share of type-\(m\) patients who patronize firm \(j\). Since \(\tilde{a}^{m*}\) and \(\tilde{a}^{l*}\) are independent of \(\lambda\), heterogeneity among firms in these shares does not affect the optimal level of use for each patient type. The per capita use for firm \(j\) is the linear combination of its usage for each type:

\[
\tilde{a}_j^* = \lambda_j \tilde{a}^m + (1 - \lambda_j) \theta(p - c) \cdot \tau (1 - H).
\]

Differentiating equation (7) with respect to \(\lambda\) illustrates that use rises in the share of type-\(m\) patients. Although \(\frac{\partial \tilde{a}_j^*}{\partial H} < 0\), the positive cross partial derivative with respect to \(H\) and \(\lambda_j\) shows that the share of type-\(m\) patients reduces the magnitude of the competition effect. Heterogeneity across firms in non-discretionary antibiotic use may cause a negative correlation across firms between the level of prescription and sensitivity of prescription to competition.

3 Context and Data

The context for this study is Taiwan, a rapidly growing economy with per capita GDP of around $30,000. Taiwan is a small and densely populated island in which 22.8 million people share an area slightly smaller than the state of Connecticut. A large mountain range separates the sparsely inhabited eastern region from population centers in the western coastal plain. Much of the population is further concentrated in the two largest cities of Taipei and Kaohsiung. Taiwan’s demographic structure and level of health are similar to other developed countries. The median age is 35.5 years and the infant mortality rate is 5.4 deaths per 1000 live births, compared to 36.6 years and 6.4 deaths in the US. In 2005, life expectancy at birth was 71.8 years for men and 77.7 years for women. Taiwan is administered through 25 cities and counties, which span the entire island and subdivide into 366 townships and districts. Subsequent references to townships include both townships and districts, while references to counties include both counties and cities. From 1997 to 2005, county boundaries did not change but townships merged or split in two instances.
Taiwan’s climate, which is subtropical in the north and tropical in the south, exhibits temperature seasonality that is typical of the Northern Hemisphere. The average temperature in January is 16 degrees (Celsius) while the average temperature in July is 29 degrees. Health care utilization also varies seasonally, with greater demand in winter months. From 1997 to 2005, 12 percent more outpatient visits occurred in January than in July. Seasonality in URIs such as colds and influenza is responsible for much of this variation, with 71 percent more visits for URIs occurring in January than in July.

In 1995, Taiwan enacted universal health care through a publicly-financed single payer insurance system. Prior to the reform, just 57 percent of the population received private health insurance coverage (Chiang 1997). Since public facilities charged for care at rates similar to private providers, many Taiwanese households were priced out of the health care market. The government implemented the 1995 reform around a fee-for-service model in which the government reimburses providers for care on behalf of patients, according to a fixed fee schedule. The system, which serves 96 percent of the population, is financed through payroll taxes and modest copayments of under $10 for outpatient visits and prescription drugs. The Bureau of National Health Insurance (BNHI) administers the program through a central office in Taipei and six regional branches.

By lowering the out-of-pocket cost of health care, national health insurance led to an increase in patient demand. Cheng and Chiang (1997) document a substantial increase in utilization, particularly among the previously uninsured, which occurred immediately after the reform. Health care utilization also increased steadily in subsequent years, with the outpatient visits growing by 1.7 percent per year from 1997 to 2002. Due to this expansion in the system, the BNHI implemented a global budget payment system in 2002 in an effort to control costs. In this adaptation of the German model, the agency caps the total expenditure in each branch and adjusts the reimbursement rate per claim so that total expenditures fall below the cap (Hsueh et al. 2004). While the global budget payment system succeeded in controlling costs, it also led to confusion among providers about the effective rate of reimbursement.

Outpatient health care markets in Taiwan mainly feature two types of firms, hospitals and clinics, that compete within geographically limited areas. Hospitals provide outpatient care through outpatient departments that are organizationally separate from other operations. These departments generate revenue directly and create demand for more lucrative inpatient services. Outpatient departments employ a median of 25 physicians, who typi-

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1 According to Benstetter and Wambach (2001), this system may exacerbate the incentive for physicians to overtreat through a large income effect on physician labor supply. In this scenario, physicians make up for lost income by submitting additional claims, further diluting the reimbursement rate per claim.
cally receive a base salary and incentives that depend upon patient volume. Hospitals offer ostensibly more thorough diagnosis and treatment, but also provide less personal service and require longer waits. Some physicians choose to operate small storefront clinics, which provide an alternative source of outpatient care. These centers are ubiquitous in urban areas and handle 72 percent of outpatient volume nationwide. They offer more personalized care than hospitals but may be unequipped to handle serious health conditions. Although travel across jurisdictions is relatively easy in Taiwan, outpatient health care markets are geographically limited by the types of illness that these providers handle. URIs such as influenza, pneumonia, and the common cold account for 32 percent of outpatient visits, and injuries account for an additional 5 percent. These conditions are either so mild or so urgent that patients are unwilling to seek care far away. Therefore, it is sensible to assume that firms compete locally for the business of patients within an area.

Many pharmacies in Taiwan are closely associated with both hospitals and clinics. Traditionally, physicians dispensed prescription drugs directly to patients. Due to concern over physician moral hazard, the government banned this practice through a fairly lenient reform in 1997. The reform, which remains the status quo, requires clinics and hospitals that distribute drugs to do so through on-site pharmacies. Firms must employ a licensed pharmacist, but the business owners continue to receive the profits from drug sales. According to Chou et al. (2003), 100 percent of hospitals and 60-70 percent of clinics operate on-site pharmacies. By allowing firms to profit directly from drug sales, this system gives physicians an incentive to encourage the use of pharmaceuticals. However, prescription drugs only account for 20 percent of total outpatient revenue. Therefore the income from drug sales may be less important for firms than consultation and diagnostic fees.

In response to surging antibiotic use, the BNHI implemented a novel policy reform in February of 2001. Before the introduction of National Health Insurance, the frequency of antibiotic use was 12-17 percent (Chang et al. 1999). Antibiotic use gradually rose in the ensuing years to a peak of 31 percent in 2000. In 1999, the newly-minted Taiwan Surveillance of Antibiotic Resistance (TSAR) reported that rates of resistance to penicillin, oxacillin, and gentamycin among certain bacteria were among the highest in the world (Ho 2005). In June of 2000, the Taiwan government began discussing a national program to confront antibiotic resistance through restrictions on antibiotic use in URIs. These conditions constitute a large share of total antibiotic use but rarely have a bacterial origin. A strategy of reducing nationwide antibiotic consumption broke with conventional resistance control, which focuses on setting the correct dosage and limiting the spread of infection. After a policy debate lasting several months, the BNHI began requiring evidence of a bacterial cause in order to reimburse physicians for antibiotics to treat URIs. After the policy change, antibiotic use
fell to 15 percent in 2002 and to 11 percent in 2005. The decline began in the second half of 2000, suggesting that physicians modified their practices in response to the policy debate (Ho et al. 2004).

Life-cycle variation in bacterial infection risk leads to large differences in antibiotic use by patient age. Figure 2 illustrates this pattern in terms of the frequency of prescription per visit and per capita. The frequency per visit, which is the primary use outcome in subsequent regressions, is the percent of outpatient visits in which the patient receives an antibiotic. Among children aged 0-9, nearly 30 percent of visits result in a prescription. The series declines monotonically through subsequent cohorts. The frequency of antibiotic use per capita is the annual number of prescriptions per patient, weighted by the patient’s total number of visits. This measure is also the highest among patients aged 0-9, but then drops off for the 10-19 cohort before rising moderately through adulthood. In terms of per capita consumption, the elderly are the second most intensive users of antibiotics. Patients over age 70 receive 32 percent more prescriptions per capita than those aged 10-19. In addition to facing the greatest incidence of bacterial infection, the young and the elderly also exhibit relatively fragile health status, which prevents doctors from awaiting laboratory confirmation of a bacterial infection before prescribing.

Variation in the intensity of use also exists on the firm side between hospitals and clinics. 13.8 percent of outpatient hospital visits lead to an antibiotic prescription, compared to 21.8 percent for clinics. On an annual per-capita basis, patients receive an average of 2.49 prescriptions from hospitals, while they receive 5.38 prescriptions from clinics. Several factors may contribute to this discrepancy, but a primary explanation is that patients sort into these facilities according to their medical needs. Though some bacterial infections are life threatening, most conditions requiring antibiotics (such as ear or urinary tract infections) are relatively mild and straightforward to treat. Patients frequently seek care for these conditions in clinics, which are more accessible and convenient. By contrast, hospital outpatient departments handle a wider array of medical conditions, which are on average more severe and difficult to diagnose.

Our analysis measures antibiotic use with outpatient claims data from 1997 to 2005. The BNHI centrally manages the reimbursement of claims for 96 percent of the population, and this database provides a comprehensive and nationally-representative picture of health care utilization in Taiwan. The data feature visit-level observations that anonymously identify the patient, physician, and township. Each record indicates the patient’s diagnosis and treatment, as well as a list of the drugs that the patient received. Claims data are available either as a 1 in 500 sample of outpatient visits or a panel of 193,000 nationally representative patients. The 1 in 500 sample is useful for calculating summary statistics.
and aggregate levels of antibiotic use. By utilizing the panel of patients, the regressions in Section 4 are able to implement patient and physician fixed effects simultaneously. Both datasets give very similar results in situations where either is applicable. Through a census of physicians, the BNHI also identifies the firm affiliation and township of each practicing doctor.

Two antibiotic prescription variables capture the absolute and relative intensity of antibiotic use. The primary measure (“antibiotics prescribed”) is an indicator that equals one if a particular outpatient visit generates one or more antibiotic prescriptions. From 1997 to 2005, patients received at least one antibiotic in 19.2 percent of visits. The secondary measure (“antibiotics share”) is the share of the drugs per visit that are antibiotics. Physicians dispense drugs in 94.2 percent of all visits and the median number of drugs dispensed is 4. By incorporating this outcome, we are able to distinguish a general effect of competition on drug use from a specific effect on antibiotics. This variable is not defined for the 5.8 percent of visits in which patients did not receive any drugs. On average, antibiotic prescriptions constitute 4.2 percent of the drugs prescribed per visit. Figure 1 plots the quarterly values of these outcomes. After a rise in antibiotic use from 1997 to 2000, prescriptions decline steeply in 2001 at the time of the policy change, and continue to fall more gradually in subsequent years. The collinearity of the two time series also reflects the high correlation (0.86) between these variables.

In keeping with previous studies of health care competition, our analysis uses the Hirschman-Herfindahl Index (HHI) to measure market concentration (Baker 2001). The HHI is defined as the sum of squared market shares across all firms in the market. The index ranges from 0 to 1 and rises with greater market concentration. A firm’s market share is defined as the percent of the physicians in the market who are employed by the firm. This definition, which reflects the firm’s short run capacity, is less sensitive to fluctuations in demand than measures based on output or revenue. In calculating the HHI, we treat townships as local health care markets. One could ideally use data on patients home locations and provider choices to group competitors into markets, but the available data, which do not identify patients’ home townships, rule out this possibility. Anecdotal evidence

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2To gauge the selection that arises from omitting these observations, we compare the characteristics of visits with zero drugs and visits with one drug. In visits with zero drugs, patients are 3.7 years younger and physicians are 2.9 years older. By 4.7 percent, these visits disproportionately occur in clinics. As discussed below, all of these characteristics are associated with a greater intensity of antibiotic use. Zero-drug visits originate in markets that, on average, have similar levels of population and market concentration to one-drug visits.

3We treat the firm, rather than the physician, as the unit of analysis because prescriptions by a particular doctor reflect the use within the firm. The correlation in antibiotic use across doctors in the same firm is 0.35, while the correlation across doctors in the same township is 0.15.
suggests that patients typically patronize clinics within their township but may sometimes visit a more distant hospital. Section 4 explores the robustness of our results to alternative definitions of market share and the market.

Hospital consolidation has driven an upward trend in market concentration over time. Panel A of Figure 3 plots the median of the HHI across townships by year and quarter, showing that median market concentration rose by 34 percent from 0.19 to 0.25 from 1997 to 2005. To investigate this trend further, Panel B plots the number of hospitals and clinics in the BNHI census in each period. The number of clinics increases by 5 percent, while the number of hospitals falls by 17 percent. Panel C then plots the number of physicians per hospital and per clinic over time, and reveals that clinics have become 30 percent larger while hospitals have grown by 150 percent. Hospital consolidation has been noted in various settings, and may reflect the long-term trend toward capital-intensive medicine (Glied 2003). Medical technology has become more elaborate and raised the fixed cost of operating a hospital. Hospitals have responded by consolidating in order to economize on these costs.

Heterogeneity in the size and number of firms contributes to cross-sectional variation in the HHI. To illustrate these differences, Table 1 divides the sample into HHI quartiles and reports the mean and standard error of several township, provider, and patient characteristics. The HHI varies considerably across townships, from 0.06 the first quartile to 0.68 in the fourth quartile. Both population and population density are several times greater in low-concentration townships, suggesting that differences in market scale contribute to variation in the HHI. Not surprisingly, the number of clinics and hospitals is greater in low-concentration townships. Areas in the first quartile feature 3.5 times as many hospitals and 5.6 times as many clinics as those in the fourth quartile. Differences in firm size also contribute to the variation in the Herfindahl Index. Hospitals in the first quartile employ 38 physicians each on average, while those in the fourth quartile employ 271 physicians. Clinics vary in size to a lesser degree. Because high-concentration townships have fewer firms but more physicians per firm, the first and fourth quartiles have similar numbers of total physicians.

Physician and patient characteristics are potentially correlated with both antibiotic use and market concentration. For instance, Huang et al. (2005) show that older physicians and younger patients use antibiotics most frequently. Older doctors may prescribe more because they are further removed from medical school training about careful use of antibiotics. Younger patients receive more prescriptions because children acquire bacterial infections—through pneumonia, cuts or ear infections—more frequently than adults. Table 1 illustrates a correlation between market concentration and these variables. Physicians are 1.7 years
older and patients are 5.8 years younger in the first quartile than in the fourth quartile. The correlation of these characteristics with both antibiotic use and market concentration suggests that other unobservable characteristics may also be correlated with these variables.

4 Market Concentration and Antibiotic Use

This section considers the effect of market concentration on antibiotic use. If antibiotics increase demand, competition may encourage physicians to prescribe antibiotics more frequently. Regressions with the following specification evaluate this hypothesis:

$$ a_{ijkt} = \beta_0 + \beta_1 H_{kt} + \beta_2 S_{jkt} + \epsilon_{ijkt} $$

Each observation is an outpatient visit for patient $i$ with physician $j$ in township $k$ and year-quarter $t$. The dependent variable, $a$, is either an indicator of whether the visit generates an antibiotic prescription (“antibiotics prescribed”) or the share of prescribed drugs that are antibiotics (“antibiotics share”). The main regressor is the Herfindahl Index, $H$, which is calculated quarterly using the number of physicians to measure firm size. All specifications also control for firm size, $S$, directly. The definition of the HHI creates a correlation between market concentration and firm size, which is evident in Table 1. By including firm size directly, the specification controls for systemic differences by size in firms’ prescription patterns.

The most important concern in estimating this specification is that heterogeneity among patients and providers may affect both market concentration and antibiotic use. The model in Section 2 highlights this issue by showing that equilibrium antibiotic use and market concentration are both functions of patient demand, $\theta$, and firm costs, $c$. A patient’s demand for antibiotics depends upon his or her health status and preferences. When aggregated across the community, both of these factors affect firm profitability, which determines the number and size of firms in the market. Variation in the disease environment is an obvious source of demand heterogeneity. Patients in areas with high disease prevalence require more antibiotics, and their demand for additional care may draw physicians to the market. Provider heterogeneity may also induce a correlation as firms and doctors self-select into markets based on characteristics that are correlated with antibiotic use. For instance, physicians who casually prescribe may practice in low-concentration markets because of the amenities of these locations.\footnote{Competition may determine the composition of providers by selecting for high-use firms. This piece of the reduced-form effect of market concentration is hard to distinguish from an effect of provider characteristics on market concentration.} Heterogeneity in either supply or demand may affect both
antibiotic use and market concentration.

We address this concern by showing results that are consistent with an effect of competition on antibiotic use and are inconsistent with a spurious correlation. OLS regressions report a negative and significant correlation between market concentration and antibiotic use. Regressions using patient and physician fixed effects, which control for time-constant heterogeneity, also show a significant effect. Time-varying heterogeneity may still induce a correlation, however results for the interaction between the HHI and the policy limiting antibiotic use are inconsistent with this possibility. The 2001 regulation, which required physicians to justify antibiotic prescriptions in URIs, increased the cost for physicians of using antibiotic prescriptions to compete. According to the model in Section 2, the effect of competition on antibiotic use declines in the costliness of prescribing antibiotics. Results for this interaction show that the effect of market concentration becomes zero after the policy change and that the timing of this decline aligns with the debate and enactment of the policy. For time-varying heterogeneity to explain this result, the correlation between this omitted variable and either antibiotic use or market concentration must coincidentally decline at the same time as the reform.

4.1 OLS and Fixed Effects

OLS and fixed effects regressions of antibiotic use on market concentration appear in Table 2. Columns 1-4 report estimates for “antibiotics prescribed” and Columns 5-8 report estimates for “antibiotics share.” All specifications control for firm size and for year-quarter effects, which absorb generalized time-series variation in competition and antibiotic use. For each outcome, the table reports estimates without fixed effects, with patient or doctor fixed effects, and with both of these combined. Coefficients and standard errors are multiplied by 100 for clarity. OLS estimates in Columns 1 and 5 reveal a negative and significant correlation between market concentration and antibiotic use. A decline in concentration of one standard deviation (0.28) is associated with a 1.2 percent greater probability that a visit leads to an antibiotic prescription and a 5.3 percent increase in the share of prescribed drugs that are antibiotics. The relevance of competition for both outcomes demonstrates that competition affects the absolute level of antibiotic use and the intensity of use relative to other drugs. The estimates also show a negative correlation between firm size and antibiotic use, which may either reflect a secular difference between large and small firms or the greater market power of large firms, conditional upon the HHI.

The remaining columns of Table 2 use patient and physician fixed effects to evaluate the robustness of this result. In Columns 2 and 6, which incorporate patient fixed effects, estimates are identified through variation in competition and antibiotic use for the same
patient. These specifications partial out time-constant differences in preferences and health status that may be correlated with market concentration. Under this approach, the effect of market concentration remains negative and statistically significant. Coefficient estimates are 14 percent smaller for “antibiotics prescribed” and 37 percent smaller for “antibiotics share.” Columns 3 and 7 control for time-constant physician heterogeneity by employing physician fixed effects. Estimates are identified through variation in market concentration and antibiotic use for the same physician, and control for factors such as the doctor’s medical training and attitude toward patients. Again, the effect of market concentration remains negative and statistically significant. The coefficient estimate for “antibiotics prescribed” is 56 percent smaller and the estimate for “antibiotics share” is 25 percent smaller than with OLS. Columns 4 and 8 control for heterogeneity in both patients and doctors by employing both patient and physician fixed effects in the same specification. Estimates are identified from variation in market concentration and usage patterns for patients who visit multiple doctors. Coefficient estimates in these regressions are similar to earlier results; the estimate for “antibiotics prescribed” is significant at the 10 percent threshold while the estimate for “antibiotics share” is significant at the 5 percent threshold. In total, these results show that time-constant heterogeneity is not responsible for the correlation between competition and antibiotic use.

4.2 A Policy Interaction

Taiwan’s 2001 reform, which limited antibiotic use in URIs, raised the cost for physicians of competing through antibiotic prescriptions. In Section 2, equation (4) shows that the effect of competition on antibiotic use declines in the costliness of offering antibiotics. Therefore, the policy change is predicted to reduce the effect of competition on antibiotic use. Table 3 presents regressions of antibiotic use on market concentration before and after the implementation of the strict regulatory policy. Columns 1-4 report estimates for “antibiotics prescribed” and Columns 5-8 report estimates for “antibiotics share.” For each outcome, the table shows specifications using OLS, patient fixed effects, physician fixed effects, and both types combined. The regressions exclude the direct effect of the policy because this variable is collinear with the time controls.

The table shows a large effect of competition on antibiotic use before the reform and roughly zero effect afterward. Columns 1 and 5 indicate that under loose regulation, a decline in concentration of one standard deviation raises the probability that a visit leads to an antibiotic by 2.4 percent and the share of prescriptions that are antibiotics by 11.3 percent. These estimates are roughly twice as large as the uninteracted estimates in Table 2. After the reform, the effect of concentration is approximately zero and is statistically insignificant.
The remaining columns illustrate the robustness of this result using patient and physician fixed effects. All specifications report the same qualitative result that tighter regulation reduces the effect of competition on prescription. In Columns 4 and 8, which incorporate both patient and physician fixed effects, coefficients remain significant but are 40 percent smaller for “antibiotics prescribed” and 21 percent smaller for “antibiotics share.” These results suggest that the policy change dramatically scaled back the practice of competitive prescription.

Although the estimates in Table 3 are consistent with an effect of competition on antibiotic use, unobserved time-varying heterogeneity could also create this pattern if the correlation between this omitted variable and either market concentration or antibiotic use diminished over time. Evidence about the timing of the decline in the effect of market concentration indicates that this scenario is unlikely. The interaction of the HHI with year-quarter dummies provides a quarterly coefficient estimate for market concentration and shows how this effect changes over time. Figure 4 plots the quarterly coefficient estimate for market concentration for both antibiotic use outcomes, based on earlier OLS specifications. The figures are coded to indicate the policy change in the first quarter of 2001. Both figures show a pronounced difference between the effect before and after the new regulation. The effect of market concentration steadily becomes larger from 1997 to 2000, and then sharply diminishes toward zero beginning in the first quarter of 2000. From 2001 to 2005, the effect is near zero and statistically insignificant. The beginning of the decrease in 2000 coincides with the policy debate preceding the policy change. In July of 1999, the National Health Research Institutes first announced alarming findings of antibiotic resistance. The subsequent discussion culminated in a high-level conference in June of 2000 to discuss the proposal that was ultimately enacted. The policy debate, which raised awareness of antibiotic resistance among physicians, may have increased the social sanction for overprescription. Physicians may have also suspected that the BNHI had begun to monitor their behavior.

Other changes in the effect of competition in Figure 4 are likely due to fluctuations in the demand for health care. Equation (4) in Section 2 illustrates that health care demand accentuates the effect of competition on antibiotic use by increasing the profit that a physician receives for attracting an additional patient. The early years of the National Health Insurance program saw steady increases in health care demand and utilization (Cheng and Chiang 1997). Figure 5 plots the quarterly aggregate patient volume and the four-quarter moving average of this series. Utilization increased from 1997 to 2000 and then remained flat through 2003, when the patient volume began to decline. Insofar as this increase in utilization reflects greater demand, it explains the rise in the effect of competition in these
years. Figure 5 also illustrates the seasonality in health care demand, which reflects greater incidence of URIs such as influenza and the common cold during winter months. Both patient volume and the effect of competition tend to be highest during the first quarter (January-March) and lowest during the third quarter (July-September). Finally, the figure shows roughly constant seasonally-adjusted volume from 2000-2002, when the government considered and adopted the antibiotics reform. This piece of evidence further suggests that the policy change was responsible for the decline in the effect of competition in this period.

The qualitative findings in this section are robust alternative definitions of market share. In the preceding analysis, the number of physicians per firm measures market share in the calculation of the Herfindahl Index. This approach, which measures the short-run capacity of the firm, is less susceptible to short-run demand fluctuations than measures based on revenue or patient volume. Regressions in which the HHI is defined in these alternate ways also show a negative effect of market concentration on antibiotic use (not reported). This effect is insignificant in the uninteracted specification. Including the policy interaction shows a negative and significant effect of competition before the policy change and roughly zero effect after the change.

The analysis above treats townships as local health care markets in order to calculate the HHI. This approach is the most convenient and nature definition in this context, but may unduly limit patients’ health care choices by assuming that they only visit hospitals within their township. A definition of the market that includes hospitals in the surrounding county as well as clinics in the township factors in competition among a larger set of hospitals. Regressions based on this market definition are qualitatively similar to earlier findings (not reported). The effect of market concentration is negative but statistically insignificant in the uninteracted specification. Estimates that include the policy interaction show a negative and significant effect prior to the policy change and no effect after the change.

4.3 Provider Discretion and Heterogeneity in Levels of Use

Section 2.3 considers how an upward cap on the level of antibiotic use per person may leave physicians treating high-use patients with little discretion over whether to offer an antibiotic. Patients for whom there is no discretion about whether to prescribe have a low elasticity of demand with respect to antibiotic use. For example, if the primary margin is whether to offer zero or one antibiotic prescriptions, competition should not affect the usage of patients with obvious bacterial infections, because these patients always obtain a prescription. Although non-discretionary demand is unobservable, this variable should induce a negative correlation between the level of use and the responsiveness to competition.

Age heterogeneity among patients generates natural variation in non-discretionary an-
tibiotic use. As Figure 2 illustrates, young children, followed by the elderly, are the most intensive users of antibiotics. This elevated level of use reflects a greater incidence of bacterial infection, as well the more fragile health status patients in these cohorts. Since much of the life-cycle variation in use arises through non-discretionary demand, the theory in Section 2.3 predicts that the effect of competition on antibiotic use should be weak for young patients, and potentially for elderly patients as well.

Table 4 evaluates this hypothesis through regressions of antibiotic use on market concentration interacted with three age cohorts: 0-9, 10-59, and 60 and over. As before, the table presents regressions for both antibiotic use outcomes using OLS, patient fixed effects, physician fixed effects, and both of types of fixed effects concurrently. The table also includes group-specific time effects, which subsume time-invariant group dummies and allow trends over time to vary by age cohort. For patients under age 10 and over age 60, there is no significant effect of competition on antibiotic use. In contrast, patients aged 10 to 59 show a large and statistically significant effect of competition on antibiotic use. This difference by age is present for both antibiotic use outcomes, and persists after controlling for patient and physician fixed effects. Based on the results in Columns 1 and 5, an increase in competition of one standard deviation raises the probability of receiving an antibiotic by 1.5 percent and increases the share of drugs that are antibiotics by 6.1 percent. These results support the theoretical framework in Section 2.3, which predicts that prescription to patients with higher rates of use should be less responsive to competition.

A further implication of the theory in Section 2.3 is that the firm’s composition of patients may affect its responsiveness to competition. As discussed in Section 3, clinics exhibit more intensive antibiotic use than hospitals. To the extent that this difference reflects greater non-discretionary demand among patients attending clinics, the effect of competition should be weaker for clinics than for hospitals. Table 5 tests this hypothesis through regressions of antibiotic use on market concentration for both hospitals and clinics. As before, the table reports estimates for both antibiotic use outcomes, employing both patient and physician fixed effects. The regressions show a large and statistically significant effect of competition for hospitals and a small and insignificant effect for clinics. In OLS regressions in Columns 1 and 5, the effect for hospitals is over five time the size of the effect for clinics. Although controlling for patient and physician fixed effects attenuates this difference considerably, the gap remains statistically significant in every regression except Column 7. Based on OLS estimates, an increase in competition of one standard deviation raises the probability of receiving an antibiotic by 4.1 percent and increases the share of

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5 The use of group-specific time effects is consistent with the specification in Table 3 since the policy change variable in those regressions does not vary cross-sectionally.
drugs that are antibiotics by 24 percent among hospitals.

5 Competition and Antibiotic Resistance

Competitive prescription of antibiotics threatens public health by exacerbating antibiotic resistance. This section gauges the effect of competition on the evolution of drug resistance by estimating a growth curve of resistance over time. A conjecture about the sensitivity of resistance growth to the level of antibiotic use allows a mapping from earlier estimates of the effect of competition into the trajectory of antibiotic resistance. This approach allows us to make an inference about the social cost of competitive prescription, which accrues through the purchase of additional drugs and the treatment of additional resistant infections.

The microbiological relationship between antibiotic use and antibiotic resistance is conclusive, though many details remain vague. In general, antibiotic use promotes resistance through two mechanisms. The presence of an antibiotic in the bacterial environment encourages genetic mutations that circumvent the drug’s antibacterial properties. Once mutations develop, antibiotics promote colonization by resistant strains by eliminating susceptible bacteria that would otherwise compete for resources. Resistant bacteria spread in the human population through interpersonal contact over the course of years and decades. Epidemiological models of this process ((Austin et al. 1997, Stewart et al. 1998)) depict a sigmoidal (s-shaped) growth path of resistance. Carrying a resistance gene is metabolically costly, and resistant strains are disadvantaged relative to susceptible strains in the absence of antibiotics. Therefore, the growth of resistance is initially increasing in the level. Once resistance attains a sufficiently high threshold, the growth rate slows as few habitats remain uncolonized.

While laboratory studies have linked antibiotic use to resistance, empirical evidence of this relationship in the community has proven elusive. Bronzwaer et al. (2002) find a correlation between levels of resistance and quantities of antibiotics sold across Europe, while Seppala et al. (1997) link erythromycin use and resistance among Streptococci in Finland. These studies are difficult to interpret in terms of epidemiological models because they do not examine the effect of antibiotic consumption on resistance growth. Moreover, population-based estimation of the effect of antibiotic use on resistance suffers serious endogeneity concerns. A natural experiment in the allocation of antibiotics would be needed to control convincingly for omitted variables that are correlated with both antibiotic use and resistance. Rather than attempt to estimate the effect of antibiotic use on resistance, we measure the effect of competition on resistance under different conjectures about how antibiotic use affects resistance growth.
5.1 A Growth Path of Antibiotic Resistance

While the causal effect of antibiotic use on resistance is difficult to estimate reliably, the accumulation of resistance over time largely reflects the use of antibiotics. This subsection estimates a growth path of antibiotic resistance by regressing resistance on drug age. The basis for this exercise is the Taiwan Surveillance of Antibiotic Resistance (TSAR), which is a biannual survey of antibiotic resistance in several dozen Taiwan hospitals from 1998 to 2006. Each hospital provides approximately 60 bacterial isolates from both inpatients and outpatients with bacterial infections. Surveillance administrators group these isolates into 20 different genera and test them for resistance against 21 antibiotics, which represent nine of the major antibiotic classes and vary in age from 2 to 63 years. Treating each isolate-drug pairing as observation yields 117,000 binary measurements of antibiotic resistance.

Estimates of the growth path of resistance are based on the following specification, in which $r$ is a binary measure of resistance and $A$ is the drug’s age in years:

$$ r_{idt} = \beta_0 + \beta_1 A_{dt} + \epsilon_{idt} $$

(9)

In this equation, $i$ indexes the isolate, $d$ indexes the drug, and $t$ indexes the calendar year. For this specification, a linear probability model has the advantage that $\beta_1$ is directly interpretable as the average annual increase in resistance in the data. However, a linear model is not ideally suited to estimate a growth curve in this context because it neglects the upper and lower bounds on resistance. Instead a logit model leads elegantly to an estimate of a sigmoidal growth curve because the logit likelihood is appropriately bounded and adheres to this shape.

Columns 1 and 2 of Table 6 report the OLS and logit estimates of equation (9). In Column 1, each additional year of age for a drug increases its resistance by 1.0 percentage points on average, an effect that is highly significant. Estimates from Column 2, when inserted into the logit likelihood, yield a sigmoidal resistance growth curve: $\hat{r}_{idt} = \exp(\hat{\beta}_0 + \hat{\beta}_1 A_{dt})/(1 + \exp(\hat{\beta}_0 + \hat{\beta}_1 A_{dt}))$. The regression underlying this curve is identified through the comparison of age and resistance profiles across drugs. Therefore the curve depicts a growth path for a hypothetical drug that loosely represents the drugs in the data. Figure 6A plots the resistance growth path implied by this estimate. In the figure, resistance has

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Isolates are only tested against drugs that are relevant for the particular bacterial genus. To test for resistance, a technician grows the isolate in the presence of different concentrations of the antibiotic. An isolate is resistant if growth occurs above a defined threshold after a period of time. Data on the age of each drug are available from the Database of Clinical Pharmacology, which provides the year of FDA approval. The drugs in the data include gentamicin, tobramycin, ceftazidime, cefazolin, ceftriaxone, cephalothin, cefuroxime, cefotaxime, trimethoprim, clindamycin, erythromycin, ampicillin, oxacillin, penicillin, piperacillin, ticarcillin-clavulanic acid, chloramphenicol, ciprofloxacin, levofloxacain, nalidixic acid, and tetracycline.
an initial level of 10 percent and accumulates rapidly to reach 64 percent after 60 years. To
gauge the quality of the fit, Figure 6B plots the mean resistance rate and age for each drug
in the data. Since the oldest drug, Penicillin, has a maximal age of 63 in the data, Figure
6A extrapolates the level of resistance beyond this point.

The growth over time in antibiotic resistance, reflected in Figure 6A, is fundamentally
the result of community-wide consumption of these drugs. Through an assumption about
the elasticity of the growth rate with respect to antibiotic use, it is possible to estimate
the effect of a change in antibiotic use on the trajectory of resistance. This approach
can provide a ballpark estimate of the impact of competitive prescription on antibiotic
resistance. Reflecting the non-linearity of the logistic growth curve, the change in resistance
over time is a non-linear function of the growth coefficient, $\beta_1$ and the age of the drug:
$$\frac{\partial r_{dt}}{\partial A_{dt}} = \frac{\beta_1}{1 + \exp(\beta_0 + \beta_1 A_{dt})^2}. $$
Through a conjecture about the elasticity of $\beta_1$ with respect to antibiotic use, it is possible to gauge the impact on resistance of a given
percentage increase in antibiotic use. Insofar as antibiotic consumption is the primary
cause of resistance growth, a unitary elasticity between use and $\beta_1$ is a natural choice.
As a sensitivity check on this assumption, we also consider the effect of consumption on
resistance under an elasticity of 0.5 and 1.5.

Under unitary elasticity between antibiotic use and $\beta_1$, an increase in antibiotic use
of one percent translates into a comparable rise in the growth coefficient. According to
the estimate in Column 1 of Table 3, an increase in competition of one standard deviation
raises antibiotic use by 2.4 percent prior to the policy change, or 9.7 percent of its initial
level. Along side the original growth curve estimate, Figure 6A plots the growth curve
implied by a 9.7 percent increase in the magnitude of $\beta_1$. This change shifts the curve
measurably to the left, hastening the onset of resistance. Since both curves asymptote to
1 by construction, the impact of greater use eventually diminishes. Figure 7 illustrates
the effect of an increase in competition of one standard deviation on the level of resistance
over time by plotting the percentage increase in resistance by drug age under elasticities
of 0.5, 1, and 1.5. Under each scenario, greater antibiotic use translates into substantially
greater resistance in the initial decades of the drug’s life. At the time of the maximal effect,
which occurs around year 42, resistance is 12 percent greater in the baseline scenario, 18
percent greater in the aggressive scenario, and 6 percent greater in the conservative scenario.
Even under conservative assumptions, competitive prescription leads to noticeably more
resistance than would have existed otherwise.
5.2 Cost Accounting

The social cost of antibiotic use includes spending on additional drugs and treatment of resistant infections. This subsection relies on the mapping from competition into resistance to calculate the cost of competitive antibiotic use through these two channels. The additional drug expenditure is straightforward to compute based on Taiwan’s annual antibiotics budget of $96.2 million. Holding fixed the basket of antibiotics consumed, a 2.4 percent increase in consumption leads to $2.3 million in additional spending on antibiotics.\(^7\) Estimates of the costs due to antibiotic resistance rely on a thought experiment in which only a single representative antibiotic is available. Society chooses a constant rate of use at the drug’s introduction and resistance develops according to the path delineated above. This scenario abstracts from heterogeneity among drugs and removes the incentive for physicians to switch into drugs with lower resistance. Calculations are based on a drug lifespan of 60 years. After this period, resistance exceeds 64 percent and limits the drug’s clinical effectiveness.

The costliness of antibiotic resistance depends upon the frequency with which antibiotics are required and the differential treatment cost per case when resistance appears. The number of antibiotic prescriptions overstates the actual number of infections since patients may obtain antibiotics multiple times for the same condition, and since physicians sometimes offer antibiotics inappropriately. Excluding URIs (ICD9 diagnosis codes of 460 to 466) and dividing by the average number of repeat prescriptions (1.92) yields an estimate of 11.3 million annual instances nationwide in which antibiotics are required. Resistant infections require additional medical care and treatment with more costly drugs. Using the claims data, we compute the total quarterly treatment cost for patients receiving antibiotics. This calculation assumes that treatment for a particular condition is limited by the quarter, and excludes inpatient expenses, which may be substantial in some cases. Patients taking antibiotics have quarterly expenses ranging from $1.50 to $77,445, with resistant cases occupying the right tail of the distribution. As a baseline, we assume that the average cost of treating a susceptible infection is drawn from the 25th percentile of this distribution ($33) and the cost of treating a resistant infection is drawn from the 75th percentile ($140). Therefore each infection that is resistant rather than susceptible has an additional social cost of $107. Multiplying this differential by the annual number of infections indicates that a one percentage point increase in resistance leads to 112,860 additional resistant infections and $12.1 million in additional medical care.

\(^7\)To obtain this estimate, we multiply the number of units dispensed in each antibiotic claim by the price per unit. The figure is the average total expenditure from 2002 to 2005. All monetary values are expressed in US dollars, which are converted from New Taiwan dollars with an exchange rate of 32 to 1.
The age-dependent effect of competition on resistance causes the social cost of competitive antibiotic use to vary over time. Figure 8 plots the annual non-discounted social cost of a 2.4 percent increase in antibiotic use. Purchasing additional drugs leads to $2.3 million in additional annual expenditures, while the cost of treating resistant infections rises with the differential effect on resistance. Annual treatment costs quickly overtake the costs of purchasing additional antibiotics and balloon to roughly $75 million by year 60 of the drug’s life. While an increase in resistance of 12 percent over the initial level may seem modest, this change translates into significantly greater medical expenditures.

Discounting these costs into present values makes it possible aggregate over the decades in which the costs are incurred. We apply a discount rate of 1.44 percent per year, which is the Bank of Taiwan’s average interbank lending rate from 2002 to 2005. A low discount rate places relatively more emphasis on the future costs of drug resistance. Table 7 reports the present discounted value of each type of cost over the 60 year life of the drug. In Column 1, which shows the baseline scenario, an increase in use of 2.4 percent leads to $94.7 million in additional antibiotics spending and $1.3 billion for the treatment of resistant infections. Below each value, the table expresses the cost as a percent of the total antibiotics budget. An increase in competition of one standard deviation causes $1.4 billion in additional expenditures, which is 35 percent of Taiwan’s antibiotics budget.

Since these estimates rely on an assumption about the differential cost of treating a resistant infection, we also use conservative and aggressive assumptions for this parameter to recalculate the discounted social cost. In the conservative scenario, a susceptible infection is drawn from the 40th percentile of the quarterly cost distribution ($51) while a resistant infection is drawn from the 60th percentile ($88). In the aggressive scenario, a susceptible case is drawn from the 10th percentile of the cost distribution ($16), while a resistant case is drawn from the 90th percentile ($273). An increase in resistance of one percent leads to additional treatment costs of $4.2 million under conservative assumptions and $29.0 million under aggressive assumptions. The conservative scenario also uses the growth curve associated with $\gamma = 0.5$ above, while the aggressive scenario uses the growth curve associated with $\gamma = 1.5$. Columns 2 and 3 of Table 5 report the present discounted cost under these alternative scenarios. Costs are 76 percent less under conservative assumptions, but still constitute 8 percent of the antibiotics budget. Expenses more than triple in the aggressive scenario, for a total of $4.9 billion over the life of the drug, or 125 percent of Taiwan’s antibiotics budget. Competitive antibiotic use remains costly under conservative assumptions, and these costs rapidly escalate under more aggressive assumptions.
6 Conclusion

This paper provides evidence of a relationship between health care competition and antibiotic use in Taiwan. Our findings, which employ both patient and physician fixed effects, and the interaction with a policy restricting antibiotic use, are consistent with an effect of competition on physician behavior and are inconsistent with competing explanations. Results show that regulation tempered the effect of competition on antibiotic use, and that competition had the greatest impact under the loose oversight prior to 2001. By raising the cost of prescribing antibiotics for physicians, the policy change dissuaded doctors from using antibiotics to compete. Results that distinguish between patients of different ages and firms of different types show that the effect of competition accrues most significantly in settings that afford physicians discretion over whether to prescribe. If a physician’s latitude to prescribe antibiotics is negatively correlated with present antibiotic consumption levels, policymakers may be most successful in controlling competitive prescription in low-usage settings such as hospitals.

Competitive antibiotic use leads to additional drug expenditures and resistant infections. The costs that arise through these channels are potentially substantial and constitute an important fraction of Taiwan’s antibiotics budget that could be directed toward other uses. The scope of this analysis is limited to costs, and further information about the benefits of additional antibiotic use would be required to make a welfare inference. Since marginal antibiotic prescriptions often target minor, non-bacterial conditions, the benefits of competitive antibiotic use are likely to be small. Our analysis does not speak to the general welfare implication of health care competition, which has many benefits that are unrelated to antibiotic use. Policies such as Taiwan’s reform that target problematic behavior can effectively address externalities from competition while preserving the positive aspects of a competitive market.
References


Table 1: Summary Statistics by Market Concentration Quartile

<table>
<thead>
<tr>
<th>Quartile (HHI)</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
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<tbody>
<tr>
<td>HHI</td>
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<td>0.15</td>
<td>0.30</td>
<td>0.68</td>
</tr>
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<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Population</td>
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<td>66,218</td>
<td>53,913</td>
<td>26,340</td>
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<tr>
<td></td>
<td>(1704)</td>
<td>(1268)</td>
<td>(1089)</td>
<td>(706)</td>
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<td>Population density</td>
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<td>119</td>
<td>131</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>(7)</td>
<td>(7)</td>
<td>(8)</td>
<td>(3)</td>
</tr>
<tr>
<td>Number of hospitals</td>
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<td>1.94</td>
<td>1.49</td>
<td>0.71</td>
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<td>(0.06)</td>
<td>(0.05)</td>
<td>(0.04)</td>
<td>(0.02)</td>
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<td>Number of clinics</td>
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<td>50.3</td>
<td>38.7</td>
<td>14.1</td>
</tr>
<tr>
<td></td>
<td>(1.49)</td>
<td>(1.28)</td>
<td>(1.08)</td>
<td>(0.56)</td>
</tr>
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<td>Physicians per hospital</td>
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<td>77.23</td>
<td>146.51</td>
<td>270.56</td>
</tr>
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<td></td>
<td>(0.64)</td>
<td>(1.58)</td>
<td>(3.71)</td>
<td>(13.37)</td>
</tr>
<tr>
<td>Physicians per clinic</td>
<td>2.19</td>
<td>2.12</td>
<td>2.25</td>
<td>2.48</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Number of physicians</td>
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<td>249.9</td>
<td>303.9</td>
<td>215.4</td>
</tr>
<tr>
<td></td>
<td>(6.53)</td>
<td>(7.82)</td>
<td>(10.09)</td>
<td>(10.74)</td>
</tr>
<tr>
<td>Age of physician</td>
<td>44.93</td>
<td>44.98</td>
<td>44.23</td>
<td>43.24</td>
</tr>
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<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Age of patient</td>
<td>35.18</td>
<td>37.30</td>
<td>39.67</td>
<td>40.98</td>
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<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.03)</td>
</tr>
</tbody>
</table>

Note: Standard errors appear in parentheses. Quartiles are calculated by township. Population is the number of people residing in the township. Population density is the number of people per square kilometer. Age of physician and age of patient are averages across individuals in each group.
Table 2: OLS and Fixed Effects Regressions of Antibiotic Use on Market Concentration

| Outcome: | Antibiotics prescribed | | Antibiotics share | | | | |
|----------|------------------------|--|------------------||--||---|---|
|          | (1)        | (2)    | (3)        | (4)    | (5)    | (6)    | (7)    | (8)    |
| HHI      | -4.24      | -3.67  | -2.02      | -3.71  | -0.77  | -0.54  | -0.58  | -0.74  |
|          | (1.28)     | (1.31) | (1.12)     | (1.02) | (0.27) | (0.23) | (0.17) | (0.18) |
| Firm size| -0.0052    | -0.0037| 0.0001     | -0.0030| -0.0010| -0.0007| 0.0002 | -0.0005|
|          | (0.0018)   | (0.0011)| (0.0003)  | (0.0012)| (0.0003)| (0.0002)| (0.0000)| (0.0002)|
| Year-quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Patient fixed effects | No | Yes | No | Yes | No | Yes | Yes |
| Physician fixed effects | No | No | Yes | Yes | No | No | Yes |
| Sample size | 20,834,120 | 20,834,120 | 20,834,120 | 20,834,120 | 19,607,042 | 19,607,042 | 19,607,042 | 19,607,042 |
| R squared | 0.028 | 0.124 | 0.220 | 0.238 | 0.016 | 0.113 | 0.184 | 0.214 |

Note: Heteroskedasticity-robust standard errors appear in parentheses. Standard errors are clustered by township. Coefficients and standard errors are multiplied by 100. "Antibiotics prescribed" is an indicator that the physician prescribed at least one antibiotic during the outpatient visit. "Antibiotics share" is the percent of prescribed drugs that are antibiotics. "HHI" is the township's sum of squared market shares, calculated by year and quarter. Market share is the percent of total physician employment attributed to the firm. "Firm size" is the number of physicians per firm (in hundreds) by year and quarter.
Table 3: OLS and Fixed Effects Regressions of Antibiotic Use on Market Concentration Before and After Greater Regulation

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHI pre-regulation</td>
<td>-8.47</td>
<td>-7.86</td>
<td>-5.43</td>
<td>-7.49</td>
<td>-1.71</td>
<td>-1.45</td>
<td>-1.41</td>
<td>-1.61</td>
</tr>
<tr>
<td></td>
<td>(1.53)</td>
<td>(1.51)</td>
<td>(1.33)</td>
<td>(1.16)</td>
<td>(0.33)</td>
<td>(0.28)</td>
<td>(0.19)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>HHI post-regulation</td>
<td>-0.31</td>
<td>0.25</td>
<td>1.14</td>
<td>-0.04</td>
<td>0.03</td>
<td>0.26</td>
<td>0.15</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>(1.27)</td>
<td>(1.08)</td>
<td>(1.21)</td>
<td>(0.98)</td>
<td>(0.29)</td>
<td>(0.18)</td>
<td>(0.21)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>Firm size</td>
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<td>-0.0039</td>
<td>-0.0004</td>
<td>-0.0033</td>
<td>-0.0010</td>
<td>-0.0007</td>
<td>0.0001</td>
<td>-0.0005</td>
</tr>
<tr>
<td></td>
<td>(0.0018)</td>
<td>(0.0011)</td>
<td>(0.0003)</td>
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<td>(0.0003)</td>
<td>(0.0002)</td>
<td>(0.0000)</td>
<td>(0.0002)</td>
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<tr>
<td>Year-quarter effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Patient fixed effects</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Physician fixed effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>F statistic: HHI pre=HHI post</td>
<td>31.13</td>
<td>40.65</td>
<td>18.98</td>
<td>33.24</td>
<td>31.73</td>
<td>46.62</td>
<td>35.98</td>
<td>53.61</td>
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<td></td>
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<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Sample size</td>
<td>20,834,120</td>
<td>20,834,120</td>
<td>20,834,120</td>
<td>20,834,120</td>
<td>19,607,042</td>
<td>19,607,042</td>
<td>19,607,042</td>
<td>19,607,042</td>
</tr>
<tr>
<td>R squared</td>
<td>0.028</td>
<td>0.124</td>
<td>0.220</td>
<td>0.238</td>
<td>0.016</td>
<td>0.113</td>
<td>0.184</td>
<td>0.214</td>
</tr>
</tbody>
</table>

Note: Heteroskedasticity-robust standard errors appear in parentheses. Standard errors are clustered by township. Coefficients and standard errors are "HHI" is the township's sum of squared market shares, calculated by year and quarter. Market share is the percent of total physician employment attributed to "HHI x regulation" is the interaction between the HHI and an indicator for the period after the increase in antibiotic regulation in the first quarter of 2001. "Firm size" is the number of physicians per firm (in hundreds) by year and quarter.
Table 4: Regressions of Antibiotic Use on Market Concentration by Patient Age Cohort

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Antibiotics prescribed</th>
<th>Antibiotics share</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>HH: age 0-9</td>
<td>-1.62</td>
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<tr>
<td></td>
<td>(1.80)</td>
<td>(2.23)</td>
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<tr>
<td>HH: age 10-59</td>
<td>-5.22</td>
<td>-5.37</td>
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<td></td>
<td>(1.28)</td>
<td>(1.32)</td>
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<td>HH: age 60+</td>
<td>0.57</td>
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<td>(1.18)</td>
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<tr>
<td>Firm size</td>
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<td>-0.0040</td>
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<tr>
<td></td>
<td>(0.0014)</td>
<td>(0.0012)</td>
</tr>
<tr>
<td>Year-quarter-group fixed effects</td>
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<td>Yes</td>
</tr>
<tr>
<td>Patient fixed effects</td>
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<td>Yes</td>
</tr>
<tr>
<td>Physician fixed effects</td>
<td>No</td>
<td>No</td>
</tr>
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<td>F statistic: HHI equal by age</td>
<td>33.25</td>
<td>29.64</td>
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<td>Sample size</td>
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<td>20,834,120</td>
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<tr>
<td>R squared</td>
<td>0.050</td>
<td>0.129</td>
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</table>

Note: Heteroskedasticity-robust standard errors appear in parentheses. Standard errors are clustered by township. Coefficients and standard errors are "HHI" is the township’s sum of squared market shares, calculated by year and quarter. Market share is the percent of total physician employment attributed to "Firm size" is the number of physicians per firm (in hundreds) by year and quarter.
Table 5: Regressions of Antibiotic Use on Market Concentration by Firm Type

<table>
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<tr>
<th>Outcome:</th>
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<th>Antibiotics share</th>
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<th></th>
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<th></th>
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<tr>
<td></td>
<td>(1)</td>
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<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
</tr>
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<td>HHI: hospitals</td>
<td>-14.58</td>
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<td></td>
<td>(2.06)</td>
<td>(1.94)</td>
<td>(1.61)</td>
<td>(1.62)</td>
<td>(0.43)</td>
<td>(0.42)</td>
<td>(0.30)</td>
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<tr>
<td>HHI: clinics</td>
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<td>-1.12</td>
<td>-0.98</td>
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<td>0.54</td>
<td>-0.10</td>
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</tr>
<tr>
<td></td>
<td>(1.23)</td>
<td>(0.89)</td>
<td>(1.30)</td>
<td>(0.72)</td>
<td>(0.31)</td>
<td>(0.21)</td>
<td>(0.23)</td>
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<tr>
<td>Firm size</td>
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<td>-0.0020</td>
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<td>-0.0007</td>
<td>-0.0004</td>
<td>-0.0004</td>
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<tr>
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<td>(0.0014)</td>
<td>(0.0012)</td>
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<td>(0.0009)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0001)</td>
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<tr>
<td>Year-quarter-group fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
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<tr>
<td>Patient fixed effects</td>
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<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
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<td>No</td>
</tr>
<tr>
<td>Physician fixed effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>F statistic: HHI (hos)=HHI (cli)</td>
<td>45.08</td>
<td>4.15</td>
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<td>8.09</td>
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<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.16)</td>
<td>(0.07)</td>
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<td>20,834,120</td>
<td>19,607,042</td>
<td>19,607,042</td>
<td>19,607,042</td>
</tr>
<tr>
<td>R squared</td>
<td>0.030</td>
<td>0.128</td>
<td>0.224</td>
<td>0.243</td>
<td>0.017</td>
<td>0.114</td>
<td>0.185</td>
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</table>

Note: Heteroskedasticity-robust standard errors appear in parentheses. Standard errors are clustered by township. Coefficients and standard errors are "HHI" is the township's sum of squared market shares, calculated by year and quarter. Market share is the percent of total physician employment attributed to "Firm size" is the number of physicians per firm (in hundreds) by year and quarter.
<table>
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<tr>
<th>Outcome:</th>
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<td>OLS (1)</td>
<td>Logit (2)</td>
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<td></td>
<td></td>
<td></td>
</tr>
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<td>Drug Age</td>
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<td>0.050</td>
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</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.010)</td>
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</tr>
<tr>
<td>Constant</td>
<td>-0.010</td>
<td>-2.397</td>
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</tr>
<tr>
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<td>(0.065)</td>
<td>(0.426)</td>
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</tr>
<tr>
<td>Sample size</td>
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<td>117,391</td>
<td></td>
</tr>
<tr>
<td>R squared</td>
<td>0.095</td>
<td>0.077</td>
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</table>

Note: Standard errors are clustered by drug and are robust to heteroskedasticity. Included drugs: gentamycin, tobramycin, ceftrizine, cefazolin, ceftriaxone, cephalothin, cefuroxime, cefotaxime, trimethoprim, clindamycin, erythromycin, ampicillin, oxacillin, penicillin, piperacillin, ticarcillin, chloramphenicol, ciprofloxacin, levofloxacin, nalidixic acid, tetracycline.
Table 7: Social Costs Due to an Increase in Competition on One Standard Deviation

<table>
<thead>
<tr>
<th>Estimate:</th>
<th>Baseline (1)</th>
<th>Aggressive (2)</th>
<th>Conservative (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Additional antibiotics purchases</td>
<td>94.3</td>
<td>94.3</td>
<td>94.3</td>
</tr>
<tr>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>Treatment of resistant infections</td>
<td>1,269.0</td>
<td>4,822.7</td>
<td>232.4</td>
</tr>
<tr>
<td>(0.32)</td>
<td>(1.22)</td>
<td>(0.06)</td>
<td></td>
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<tr>
<td>Total</td>
<td>1,363.3</td>
<td>4,917.0</td>
<td>326.7</td>
</tr>
<tr>
<td>(0.35)</td>
<td>(1.25)</td>
<td>(0.08)</td>
<td></td>
</tr>
</tbody>
</table>

Note: the percent of total antibiotics expenditures appears in parentheses. All estimates are in millions of US dollars, converted to present discounted values using the Taiwan's interbank lending rate of 1.44 percent.
Figure 1: Quarterly Antibiotic Use: 1997-2005

[Graph showing quarterly antibiotic use from 1997 to 2005 with two lines representing percent of outpatient visits and percent of drugs per visit over the years.]

Legend:
- Blue line: Antibiotics Given
- Orange line: Antibiotics Share
Figure 2: Intensity of Antibiotic Use by Patient Age

- Percent of Outpatient Visits
- Number of Prescriptions per Year
- Annual Antibiotic Prescriptions Per Capita
Figure 3A: Median Market Concentration Over Time

Figure 3B: Number of Firms: 1997-2005
Figure 3C: Number of Providers Per Firm: 1997-2005

The graph illustrates the number of physicians per hospital and clinic from 1997 to 2005. The data shows an increasing trend for physicians per hospital and a more fluctuating trend for physicians per clinic.
Figure 4A: Effect of Market Concentration on "Antibiotics Prescribed": 1997-2005

Figure 4B: Effect of Market Concentration on "Antibiotics Share": 1997-2005
Figure 5: Quarterly Volume of Outpatient Visits: Total and 4-Quarter Moving Average
Figure 6A: The Estimated Path of Antibiotic Resistance and the Path Implied by an Increase in Competition of One Standard Deviation

Figure 6B: Drug Ages and Levels of Resistance in 1998
Figure 7: Percentage Increase in Resistance Due to an Increase in Competition of One Standard Deviation: Estimates Using Different Elasticities
Figure 8: Additional Annual Costs of an Increase in Competition of One Standard Deviation