

Health Care Competition, Antibiotic Use, and Antibiotic Resistance in Taiwan*

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Abstract

While antibiotics are critical to modern health care, their overuse has fostered antibiotic resistance. Since patients in many settings prefer to visit doctors who freely prescribe antibiotics, doctors may have an incentive to attract patients through greater prescription. This paper examines the effect of health care competition on antibiotic prescription in a large, nationally-representative sample of outpatient visits from Taiwan. We find that an increase in competition of one standard deviation raises antibiotic use by up to 2.4 percent, but that the government's response of greater physician regulation successfully eliminates this effect. The paper relies on multiple results, including regressions with both patient and physician fixed effects and two theoretically-derived interactions, to rule out alternative explanations for this finding. Using these estimates, we calibrate the effect of competitive prescription on antibiotic resistance. An increase in competition of one standard deviation elevates resistance by up to 11.5 percent and leads 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. The introduction of antibiotics led to dramatic gains in public health, with US life expectancy rising from 62.9 years to 68.2 years from 1940 to 1950 (Arias 2006). Antibiotics have become a cornerstone of medical care, and many courses of treatment would be impossible without them. Antibiotics are indicated for a variety of illnesses including pneumonia, tuberculosis, gonorrhea, and urinary tract infections, and are widely used prophylactically during surgery. A typical course, which may last for several days, can eliminate an infection with fewer risks or side effects than other, more invasive alternatives. A downside of the pervasive use of antibiotics has been the development of drug-resistant pathogens. Since bacteria reproduce in matter of hours and days, they quickly evolve 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 global public health by increasing the cost and challenge of treating bacterial infections. As many first-line antibiotics have aged, high rates of resistance have eroded their effectiveness. Erythromycin is a common treatment for *S. pneumoniae* infections such as pneumonia and meningitis. However, resistance of *S. pneumoniae* to erythromycin is now 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 may develop complications that require more elaborate and burdensome treatments. Lautenbach et al. (2001) find that drug resistance postpones the delivery of effective treatment by an average of 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 widely-reported study, Klevens et al. (2007) indicate that deaths due to methicillin-resistant *S. aureus* (MRSA) now outnumber deaths due to AIDS, Parkinson's Disease, emphysema, and homicide in the US. Despite these concerns, investment in the development of new antibiotics continues to decline. Spellberg et al. (2004) find that FDA approval of new antibiotic treatments has declined by 56% over the past 20 years, and that antibiotics comprise only 6 of 506 drugs currently under development at the largest drug companies.

This study examines the effect of health care competition on antibiotic use and resistance in Taiwan. Due to historically intensive antibiotic use, resistance in Taiwan is more severe than either the US or Europe (Lauderdale et al. 2004). For instance, among the

aforementioned *S. pneumonia*, resistance is 86% for erythromycin, 59% for penicillin, and 93% for tetracycline (McDonald et al. 2004). Taiwan's universal health care system, implemented in 1995, has further encouraged antibiotic consumption by heavily subsidizing health care. In response to escalating antibiotic use in the late 1990s, the government enacted a regulation in 2001 to limit antibiotic prescription. The policy, which successfully cut antibiotic use, was an innovation on prior initiatives to staunch the spread of resistance.

Competition among providers may lead to greater antibiotic use if patients seek out doctors who liberally prescribe antibiotics. Observers have noted that this scenario aptly depicts the outlook of many Taiwanese patients. Ho (2005, p. 246) describes a typical visit:

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.

With a copayment of less than \$5, patients have a low search cost and may easily "shop" among providers for the one who is the most accommodating (Chen et al. 2006). Under these conditions, a physician who withholds antibiotics from his patients, whether prudently or not, risks losing the patients to other providers.

Focus groups of physicians based in the US similarly depict a tension between patients who demand antibiotics and physicians who would rather not dispense them inappropriately (Butler et al. 1998). In one clinician's opinion, "You can't just say 'It's viral, you don't need antibiotics, go away,' because [patients] feel they're being fobbed off. They feel that their illness is not being taken seriously." Another physician elaborates, "It does make me feel uncomfortable. I do feel as though I've been slightly used. Sometimes slightly abused as well." Another US-based survey finds that 96 percent of pediatricians receive inappropriate requests for antibiotics and one third comply with these requests at least occasionally (Bauchner et al. 1999). Therefore, doctors may feel that they can win the favor of patients by dispensing antibiotics freely.

Competition accentuates the provider's incentive to prescribe by increasing his elasticity of demand. Attracting patients through prescription is a form of quality competition, where "quality" refers to any aspect of the visit that the patient finds valuable. A firm with a low elasticity of demand receives only a small benefit from a quality improvement while a firm with a high elasticity of demand receives a large benefit. Analogously to a standard model, a monopolist has a diminished incentive to improve quality because the firm must also offer

this quality level to inframarginal consumers. This simple theory predicts that competition may increase the intensity of antibiotic prescription.

Several papers in the industrial organization literature have examined the theoretical effect of competition on product quality. In general, competition raises quality if a quality improvement increases the firm's demand. Spence (1975) proves that a monopolist produces too little quality when its price is regulated. The firm's optimal quality choice rises in its elasticity of demand, so that quality is higher when the monopolist has less market power. This result generalizes to the oligopoly case as long as firms cannot compete through prices (Dorfman and Steiner 1954, Beil et al. 1995). The health economics literature has considered the effect of competition on quality, but never in the context of outpatient care or prescription. Robinson and Luft (1985) sparked a debate about the so-called medical arms race, in which competition leads hospitals to invest in expensive equipment, which drives up the cost of health care (Dranove and Satterthwaite 2000, Section 4.2). Since the price of care is not fixed in general, competition may either increase or decrease quality. However, Propper, Burgess and Green (2004) show with hospital mortality records that UK hospitals have responded to competition by modestly reducing quality. By examining antibiotic use, we broaden this inquiry beyond the context of hospital-based care in developed countries.

This study utilizes claims data from Taiwan's Bureau of National Health Insurance (BNHI), which is a particularly strong data source. In the process of managing and paying claims, the BNHI tracks health care utilization for 96 percent of Taiwan's population who use the system. Our analysis is based on a panel dataset containing all outpatient visits from 1997 to 2005 for a nationally representative sample of 200,000 patients. The data also include a census of health care providers, from which we construct a Hirschman-Herfindahl Index (HHI) of market concentration. These data allow us to regress antibiotic use by visit on market concentration while controlling simultaneously for patient and physician fixed effects. The paper also employs antibiotic resistance data that are available through a surveillance of two dozen hospitals across Taiwan.

The paper proceeds in Section 2 by illustrating the effect of competition on antibiotic use in a simple model. By endogenizing the entry decision, we solve for market concentration and antibiotic use in terms of demand and supply parameters. This approach shows which variables may induce a spurious correlation between competition and antibiotic prescription. Section 3 describes the context and the data and Section 4 presents regressions of antibiotic use on market concentration. These regressions show a negative and significant effect of market concentration on antibiotic prescription. The main concern in these regressions is that heterogeneity in demand or supply parameters may generate a spurious correlation. Physician and patient fixed effects control for time-constant characteristics, limiting

the concern to time-varying heterogeneity. To examine whether time-varying heterogeneity may confound the result, we examine the interaction between market concentration and two important variables. An interaction with the enhanced 2001 regulation of antibiotics shows that, as predicted, tighter regulation attenuates the effect of competition on prescription. Another interaction with the age of the patient shows that the largest effect of competition occurs among middle-aged patients, whose prescription is subject to the greatest discretion. As discussed below, these findings are consistent with an effect of competition on prescription and are inconsistent with alternative mechanisms.

Finally, Section 5 estimates the cost of competitive antibiotic prescription. We use data from a nationwide surveillance of antibiotic resistance to estimate a growth curve of resistance over time. If resistance growth has a unitary elasticity with respect to antibiotic consumption, then an increase in competition of one standard deviation, which raises use by 2.4 percent, increases resistance by up to 11.5 percent, depending on the drug’s age. Under assumptions about the additional treatment costs of infections that are resistant, 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 that follows, competition encourages physicians to prescribe antibiotics in order to attract patients. Since existing studies examine competition and product quality in general (Spence 1975, Beil et al. 1995), this section provides intuition for the present context. We adapt a standard Cournot model by assuming that the government fixes the price of health care. Within a random utility framework, patients receive positive utility from antibiotics. 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, $\phi > 0$, who are indexed by i and each demand $\theta > 0$ units of health care. $n \geq 0$ homogeneous firms, indexed by j , completely satisfy the market’s health care demand. Patients have both a discretionary and non-discretionary demand for antibiotics. The patient’s non-discretionary demand, $\lambda \geq 0$ reflects the medical need to use antibiotics for treatment and is not a choice variable for the firm. In addition to this amount, firms compete for patients by offering discretionary antibiotic prescriptions, $a_j \geq 0$. Since the market contains ϕ patients who patronize n firms, it is important to distinguish between per-firm antibiotic use, a_j , and per capita

antibiotic use, $\tilde{a}_j = na_j/\phi$. Consistent with this notation, $\tilde{\lambda} = n\lambda/\phi$ represents per-capita non-discretionary use. The patient's utility is a function of his antibiotic consumption and the quality of the provider-patient match, ν_{ij} : $u(\tilde{a}_j, \tilde{\lambda}, \nu_{ij}) = \ln(\tilde{a}_j + \tilde{\lambda}) + \nu_{ij}$. Under the assumption that ν_{ij} has a Type-II Extreme Value distribution, firm j 's demand depends upon the intensity of its antibiotic use relative to other firms: $q_j = \phi \theta \times (a_j + \lambda) / \sum_{k=1}^n (a_k + \lambda)$ (McFadden 1974).

The expression for the firm's profits follows easily from this firm demand function. For each unit of health care, a firm receives compensation $p > 0$ and incurs cost $c \in [0, p)$. Suppose that the firm also incurs cost τ for every unit of antibiotics that it offers. This cost represents the regulatory oversight of antibiotic use and reflects per-firm rather than per-capita antibiotic consumption. Firm j maximizes the following profit function with respect to a_j :

$$\max_{a_j} \pi_j = \theta \phi (p - c) \frac{a_j + \lambda}{\sum_{k=1}^n a_k + \lambda} - \tau (a_j + \lambda) \quad (1)$$

For the main analysis that follows, we assume that non-discretionary antibiotic use, $\tilde{\lambda}$, equals zero. However, Section 2.3 below elaborates on how this parameter limits the ability of doctors to attract patients with antibiotics. 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 .

$$a^* = \frac{\theta \phi (p - c)}{\tau} \times \frac{n - 1}{n^2} \quad (2)$$

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/ϕ provides an expression for equilibrium antibiotic use per capita, \tilde{a}^* . One can equivalently express antibiotic use 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 $H = \sum_{k=1}^n 1/n^2 = 1/n$:

$$\tilde{a}^* = \frac{\theta (p - c)}{\tau} \times (1 - H) \quad (3)$$

Equation (3) shows how the factors in the model determine antibiotic use. Antibiotic use is increasing in the demand for health care, θ and the profit margin, $p-c$, but use is decreasing in the intensity of regulation, τ . Since the expression normalizes by population, per-capita antibiotic use does not depend upon the number of patients in the market.

Differentiating this equation with respect to H shows that antibiotic use is decreasing in market concentration.

$$\frac{\partial \tilde{a}^*}{\partial H} = -\frac{\theta(p-c)}{\tau} < 0 \quad (4)$$

Intuitively, an increase in H reduces the elasticity of demand for firms that remain in the market. A firm considering whether to increase a_j attracts fewer patients through this action when market concentration is high than when market concentration is low.

Equation (4) also illustrates how the factors in the model mediate the effect of competition on antibiotic use. The cost of prescribing antibiotics, τ , appears in the denominator of the expression, which shows that regulation attenuates the effect of competition on prescription. We directly test this implication in Section 4 by examining the effect of competition on prescription before and after the 2001 policy change, in which the government tightened the regulation of prescription. Since τ also appears in the denominator of equation (3), regulation also directly reduces the level of prescription. In contrast, the demand for health care, θ , has the opposite effect on both antibiotic use and the role of competition. Greater patient demand accentuates the firm's profit motive to entice patients 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 κ . 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:

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

This expression shows how the Herfindahl Index depends upon the parameters of the model. The entry barrier, κ and the cost of care, c , both positively affect H . Market concentration is decreasing in patient demand, θ , and the reimbursement rate, p . Under the assumption that the cost of offering antibiotics, τ , 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, θ , enters the denominator of H^* and the numerator of \tilde{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, κ , as a source of exogenous variation in H since this variable affects the Herfindahl Index but not per capita antibiotic use.

The derivations of \tilde{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 Non-Discretionary Demand

This subsection illustrates how limiting physician discretion raises antibiotic use and reduces the effect of competition on prescription. If a patient has a medical condition that clearly requires antibiotics, he or she will use antibiotics intensively but will not choose a provider according to the provider's willingness to prescribe. The role of discretion has an implication

for the effect of competition across the patient age distribution. Doctors have relatively little discretion over prescription for young and elderly patients because these cohorts are more vulnerable to infection on average. Section 4.3 below tests this prediction with regressions that interact market concentration with the patient’s age.

Section 2.1 derives the solution to the model under the assumption that non-discretionary demand, λ , is zero. Solving the model without this constraint leads to a possible corner solution for \tilde{a}^* :

$$\tilde{a}^* = \max\left\{\frac{\theta(p-c)}{\tau}(1-H) - \tilde{\lambda}, 0\right\} \quad (6)$$

In this expression, total per-capita antibiotic use, $\tilde{a}^* + \tilde{\lambda}$ equals the amount on the right hand side in equation (3) as long as $\tilde{\lambda}$ is small. However, non-discretionary demand crowds out discretionary demand one-for-one, and the non-negativity constraint on a_j means that a sufficiently large $\tilde{\lambda}$ may force \tilde{a}^* to zero. In this scenario, the patient’s total antibiotic use equals $\tilde{\lambda}$.

This possible corner solution creates a discontinuity in the effect of competition on prescription. For low values of $\tilde{\lambda}$, $\partial\tilde{a}^*/\partial H = -\theta(p-c)/\tau$ as before in Equation (4). For values of $\tilde{\lambda}$ that exceed $\frac{\theta(p-c)}{\tau}(1-H)$, the effect of competition on prescription is zero. An increase in non-discretionary demand attenuates the effect of competition by increasing the prospect that this constraint will bind. Patients with large values of λ may obtain antibiotics anywhere, which removes the incentive for physicians to use these drugs as an enticement. This result implies that the effect of competition on prescription is weakest for young and elderly patients.

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.

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 \$5 for outpatient visits and prescription drugs. The 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. As the system expanded, the BNHI implemented a global budget payment system in 2002 in order 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).¹ 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 primarily 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 typically 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 ar-

¹According 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.

eas 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, between 12-17 percent of outpatient visits resulted in an antibiotic prescription (Chang et al. 1999). Antibiotic use gradually rose in the ensuing years to a peak of 31 percent in 2000. In 1999, the just-completed Taiwan Surveillance of Antibiotic Resistance (TSAR) reported that rates of resistance to penicillin, oxacillin, and gentamicin 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).

Whether to prescribe an antibiotic is often a judgement call for the physician. Many

patients arrive reporting vague symptoms such as fever or cough that may or may not indicate a bacterial infection. For a definitive diagnosis, the physician must request a culture of the bacteria, which requires a technician to grow the suspected pathogen in the lab (Fitch 2002). Rather than wait for test results, which may take 2-3 days to arrive, many physicians practice “empirical antibiotic therapy,” in which they prescribe antibiotics preemptively and use the patient’s response as a *de facto* diagnostic technique. Physicians have the greatest discretion over whether to prescribe antibiotics when the patient’s health status will permit a delay to await further information. According to a widely used medical handbook on infectious disease treatment, “A very important factor in the decision to use antibiotics is the urgency of the problem. The otherwise healthy patient with mild illness and no focal findings does not require treatment until a diagnosis has been reached... In contrast a patient with presumed infection who is severely ill needs immediate therapy.” (Reese and Betts, eds 1996, p. 1060) For the patient, the downside of taking antibiotics is the small risk of an allergic reaction, since antibiotic use does not change the individual’s likelihood of contracting a drug-resistant infection in most cases. Therefore, many doctors view the use of antibiotics in questionable situations as a cautious and conservative approach.

Young children and the elderly are the most intensive users of antibiotics in Taiwan. While Taiwanese patients receive an average of 4.5 antibiotic prescriptions per year (an overwhelming figure by Western standards), those aged 0-9 receive 10 prescriptions on average, while those over age 70 receive 5.5. Young children and the elderly use antibiotics intensively because they are the most vulnerable to infection and face the greatest risk of subsequent complications. According to Van Der Meer and Kullberg (2002, p. 22), “Human beings are most susceptible to infection at the two extremes of life. Neonates can be considered compromised hosts since they have...immature host defense mechanisms.” The elderly face greater susceptibility through “a decline in the quality of the [skin and mucous membrane], reduced vitality, increased risk for trauma, and a retardation in the repair process.” Given the fragile health status of both young and old patients, physicians have little discretion over whether to prescribe antibiotics to these cohorts. Patients cannot afford to wait two or more days for test results that could rule out a bacterial infection. Therefore, doctors frequently prescribe antibiotics to these groups as a precautionary measure.

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 view 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.² 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.³ In calculating the HHI, we treat townships as local health care markets. One could ideally use data on patients home

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.

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 suggests that patients typically patronize clinics within their township but may sometimes visit a more distant hospital. Section 4.4 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. In addition, the BNHI's reimbursement policies, which provide more funding to larger hospitals, have encouraged consolidation (Lu and Hsiao 2003).

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 in 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 the firm’s demand, competition may encourage physicians to prescribe antibiotics intensively. Regressions with the following specification evaluate this hypothesis:

$$a_{ijkt} = \beta_0 + \beta_1 H_{kt} + \beta_2 S_{jkt} + \epsilon_{ijkt} \quad (7)$$

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, θ , 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.⁴ 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 characteristics of doctors and patients, also show a significant effect. Since time-varying heterogeneity remains as a source of bias in these regressions, we go on to consider the interaction between market concentration and two additional variables. The 2001 regulation of antibiotic prescriptions for URIs raised the cost for physicians of using antibiotics to compete for patients. The model in Section 2 predicts that such a change reduces the effect of competition on prescription. Results for this interaction show that coefficient on market concentration goes to zero at the time of 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.

An interaction between market concentration and patient age provides further evidence by ruling out possible bias due to disease heterogeneity. Since bacterial infections are usually transitory, the fixed effects approach cannot fully control for the disease environment. Under the hypothesis that disease fluctuations spuriously induce the correlation between the HHI and antibiotic use, it is possible that the 2001 policy change attenuates the effect of competition by differentially reducing prescription in high-disease areas, which happen to be more competitive. An interaction between the HHI and patient age cohorts directly addresses this concern. If omitted variable bias related to the disease environment spuriously drives the effect of competition, then the effect of competition should be greatest among young and elderly cohorts, for whom prescription is the most sensitive to the disease environment. In contrast, Section 2.3 predicts that the effect of competition should be greatest in the middle of the age distribution, since this cohort has the smallest non-discretionary demand. Estimates show a large effect of competition for middle-aged patients and approximately zero effect for the young and elderly. This finding is consistent with an effect of competition on prescription and inconsistent with a spurious correlation due to disease heterogeneity.

⁴Competition 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.

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 significance of the effect 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 under 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 omit 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. 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 indicate 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 has diminished over time. Evidence about the timing of the decline in the effect of market concentration indicates that in fact the policy change was responsible for the decline. Interacting 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.

Fluctuations in the demand for health care are the likely cause of the remaining variation in the effect of competition in Figure 4. According to equation (4), health care demand accentuates the effect of competition on prescription by enhancing the physician's profit motive. Health care demand and utilization steadily increased during the early years of the National Health Insurance program (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 arises through greater wintertime incidence of influenza and the common cold. 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 patient volume from 2000-2002, when the government considered and adopted the antibiotics reform. This observation reinforces the conclusion that the policy change, rather than a demand shock, is responsible for the decline in the effect of competition during this period.

4.3 The Effect of Competition by Patient Age

The most problematic omitted variable in regressions of antibiotic use on market concentration is the disease environment. The prevalence of communicable diseases leads to antibiotic use while encouraging providers to enter the market, potentially inducing a spurious negative correlation between prescription and market concentration. This subsection argues against this possibility directly through regressions of antibiotic use on the interaction between the HHI and patient age. Since the strength of the immune system rises and then falls over the life course, a patient's age is a proxy for his or her vulnerability to communicable diseases. Patients at the tails of the age distribution have a greater non-discretionary antibiotic demand, λ . Therefore, Section 2.3 predicts that the effect of competition on prescription should be the greatest for patients in the middle of the age distribution.

This prediction contrasts with the impact of omitted variable bias that arises through the disease environment. Young and elderly patients, whose immune systems are more likely to be compromised, face the greatest risk of contracting communicable diseases. Therefore, the antibiotic use of young and elderly patients should be relatively sensitive to disease conditions while the use of adolescents and non-elderly adults should be relatively insensitive. Although the disease environment is not directly observable in the data, it is possible to observe how patients of different ages respond to seasonal disease fluctuations. Figure 5 plots monthly antibiotic use per capita for three age cohorts, (1) less than 10, (2) age 10 to 60, and (3) age greater than 60. Since children use antibiotics twice as frequently as the other groups, the figure normalizes consumption by the annual average for each cohort. Prescription rises for all groups in the winter months of December through March, when influenza, the common cold, and other respiratory infections are prevalent.⁵ The seasonality is most pronounced for the young cohort, for whom prescription is nearly twice as high in January as in August. The middle and elderly cohorts exhibit a similar, but less exaggerated seasonal pattern. According to the figure, the young. Based on observable seasonal variation, the middle cohort is relatively insensitive to the disease environment. If unobservable disease patterns explain the negative coefficient on the HHI, then this effect should be weaker for the middle cohort than the young cohort.

Regressions of antibiotic use on the interaction between market concentration and patient age appear in Table 4. The specification includes cohort-specific time effects, which control for differences across cohorts in usage levels and trends. As above, results for “antibiotics prescribed” appear in Columns 1-4 while results for “antibiotics share” appear in Columns 5-8. For each outcome, the table shows an OLS specification, followed by specifications that control for patient and physician fixed effects. Results clearly show that the effect of competition on prescription is strongest for the middle cohort. Among patients aged 10 to 60, a decline in concentration of one standard deviation raises the probability of prescription by 1.5 percent and the share of prescribed drugs that are antibiotics by 6.5 percent. There is no significant effect of competition for the other cohorts, and tests unambiguously reject the hypothesis that the coefficient on the HHI is equal across groups. To confirm that this result is insensitive to the choice of cut points in the age distribution, Figure 6 plots the coefficient on market concentration by decade of patient age in an OLS specification. The effect is U-shaped, with the greatest magnitude among patients aged 30-39, and no effect for those under age 20 or over age 60. These results are consistent with a lack of provider discretion for the young and elderly cohorts, but they are inconsistent

⁵The dip in antibiotic use in February corresponds to Chinese New Year, when both doctors and patients travel to visit relatives and many facilities are closed.

with omitted variables bias arising through the disease environment.

4.4 Additional Robustness Tests

Several additional robustness tests support the paper’s findings. The Herfindahl Index is a standard measure of market concentration that has been applied frequently in the health care setting. Nonetheless, one may worry that the results presented above are sensitive to the choice of this particular index. The four-firm concentration ratio is an alternative market concentration index, which is defined as the market share of the four largest firms (Tirole 1988, p. 221). The correlation in the data between the HHI and this index is 0.81. Regressions using the four-firm concentration ratio yield results that are similar to regressions using the HHI both in terms of magnitude and significance (not reported). Market concentration has a negative and significant effect on prescription that becomes stronger after including the policy interaction. This effect is isolated within the middle age cohort, with no effect for young or elderly patients.

In the preceding analysis we calculate the HHI using the number of physicians per firm to measure each firm’s market share. This approach, which captures 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), although the effect is insignificant in the uninteracted specification. Interacting the alternate HHI with the policy change leads to a negative and significant effect before the change and roughly zero effect afterward. Interacting this measure with age cohort dummies provides a negative and significant effect for the middle cohort only.

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 allows for 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. Estimates that include an interaction with age cohorts show a negative and significant effect for the middle cohort and no effect for the young or elderly cohorts.

5 Competition and Antibiotic Resistance

Competitive prescription of antibiotics threatens public health by exacerbating antibiotic resistance. This section measures 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.

Antibiotic resistance is a negative externality associated with antibiotic use. Elbasha (2003) estimates that the social cost of excessive consumption of amoxicillin (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 the positive externality of reducing 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.

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 depict a sigmoidal (s-shaped) growth path of resistance (Austin et al. 1997, Stewart et al. 1998). 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 genres 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.⁶ 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:

$$r_{idt} = \beta_0 + \beta_1 A_{dt} + \epsilon_{idt} \quad (8)$$

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 β_1 is directly interpretable as the average annual increase in resistance in the data. However, a linear

⁶Isolates 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, ceftazolin, ceftriaxone, cephalothin, cefuroxime, cefotaxime, trimethoprim, clindamycin, erythromycin, ampicillin, oxacillin, penicillin, piperacillin, ticarcillin-clavulanic acid, chloramphenicol, ciprofloxacin, levofloxacin, nalidixic acid, and tetracycline.

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 (8). 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 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, 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, β_1 and the age of the drug: $\partial r_{idt} / \partial A_{dt} = \beta_1 / (1 + \exp(\beta_0 + \beta_1 A_{dt}))^2$. Through a conjecture about the elasticity of β_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 β_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 β_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 β_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.

⁷To 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.

This calculation assumes that treatment for a particular condition is contained within one 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.

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 to 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 two theoretically-grounded interactions, 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 by patient age indicate that competition has the strongest effect when doctors have discretion over whether to prescribe.

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. This analysis focuses on costs, however a welfare inference would require additional information about the benefits of competitive prescription. Since marginal antibiotic prescriptions often target minor, non-bacterial conditions, the benefits of this phenomenon 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

- American Society for Microbiology**, “Report of the ASM Task Force on Antibiotic Resistance,” *Antimicrobial Agents and Chemotherapy*, 1995, *39*, S1–S23.
- Arias, Elizabeth**, “United States Life Tables, 2003,” *National Vital Statistics Reports*, April 2006, *54* (14).
- Austin, D. J., M. Kakehashi, and R. M. Anderson**, “The Transition Dynamics of Antibiotic Resistant Bacteria: the Relationship Between Resistance in Commensal Organisms and Antibiotic Consumption,” *Proceedings of the Royal Society of London (Biological Sciences)*, November 1997, *264*, 1629–1638.
- Baker, Laurence C.**, “Measuring Competition in Health Care Markets,” *Health Services Research*, April 2001, *36* (1), 223–251.
- Bauchner, Howard, Stephen I. Pelton, and Jerome O. Klein**, “Parents, Physicians, and Antibiotic Use,” *Pediatrics*, February 1999, *103* (2), 395–401.
- Beil, Richard O., David L. Kaserman, and Jon M. Ford**, “Entry and Product Quality Under Price Regulation,” *Review of Industrial Organization*, 1995, *10*, 361–372.
- Benstetter, Franz and Achim Wambach**, “Strategic Interactions in the Market for Physician Services: the Treadmill Effect in a Fixed Budget System,” March 2001. CESifo Working Paper Number 427.
- Bronzwaer, S. L., O. Cars, U. Buchholz, S. Molstad, W. Goettsch, I. K. Veldhuijzen, M. J. Sprenger, J. E. Degener, and the European Antimicrobial Resistance Surveillance System**, “A European Study on the Relationship Between Antimicrobial Use and Antimicrobial Resistance,” *Emerging Infectious Diseases*, March 2002, *8* (3), 278–282.
- Butler, C. C., S. Rollnick, R. Pill, F. Maggs-Rappaport, and N. Slott**, “Understanding the Culture of Prescribing: Qualitative Study of General Practitioners’ and Patients’ Perceptions of Antibiotics for Sore Throats,” *BMJ*, September 1998, *317* (7159), 637–642.
- Chang, Shan-Chwen, Hong-Jen Chang, and Mei-Shu Lai**, “Antibiotic Use in Primary Care Units in Taiwan,” *International Journal of Antimicrobial Agents*, January 1999, *11* (1), 23–30.
- Chen, Tzeng-Ji, Li-Fang Chou, and Shinn-Jang Hwang**, “Patterns of Ambulatory Care Utilization in Taiwan,” *BMC Health Services Research*, May 2006, *6* (54).
- Cheng, Shou-Hsia and Tung-Liang Chiang**, “The Effect of Universal Health Insurance on Health Care Utilization in Taiwan. Results from a Natural Experiment,” *Journal of the American Medical Association*, July 1997, *278* (2), 89–93.

- Chiang, Tung-Liang**, “Taiwan’s 1995 Health Care Reform,” *Health Policy*, March 1997, *39* (3), 225–239.
- Chou, Y. J., W. C. Yip, C. H. Lee, N. Huang, Y. P. Sun, and H. J. Chang**, “Impact of Separating Drug Prescribing and Dispensing on Provider Behaviour: Taiwan’s Experience,” *Health Policy and Planning*, September 2003, *18* (3), 316–329.
- Dorfman, Ariel and Peter O. Steiner**, “Optimal Advertising and Optimal Quality,” *American Economic Review*, December 1954, *44* (5), 826–836.
- Dranove, David and Mark A. Satterthwaite**, “The Industrial Organization of Health Care Markets,” in A. J. Culyer and J. P. Newhouse, eds., *Handbook of Health Economics, Volume 1*, 2000, pp. 1093–1139.
- Elbasha, Elamin H.**, “Deadweight Loss of Antibiotic Resistance Due to Overtreatment,” *Health Economics*, February 2003, *12* (2), 125–138.
- Fitch, R.**, “Bacterial Resistance—The Clinical Challenge,” *Clinical Microbiology and Infection*, 2002, *8*, 21–32.
- Glied, Sherry**, “Health Care Costs: On the Rise Again,” *Journal of Economic Perspectives*, 2003, *17* (2), 125–148.
- Ho, Monto**, *Several Worlds: Reminiscences and Reflections of a Chinese-American Physician*, World Scientific Publishing Company, 2005.
- , **Chao Agnes Hsiung, Hui-Tzu Yu, Cheng-Liang Chi, and Hong-Jen Chang**, “Changes Before and After a Policy to Restrict Antimicrobial Usage in Upper Respiratory Infections in Taiwan,” *International Journal of Antimicrobial Agents*, May 2004, *23* (5), 438–445.
- Horowitz, John B. and H. Brian Moehring**, “How Property Rights and Patents Affect Antibiotic Resistance,” *Health Economics*, June 2004, *13* (6), 575–583.
- Hsueh, Ya-Seng A., Shoou-Yih Lee, and Yu-Tung A. Huang**, “Effects of Global Budgeting on the Distribution of Dentists and Use of Dental Care in Taiwan,” *Health Services Research*, December 2004, *39* (6), 2135–2153.
- Huang, N., Y. J. Chou, H. J. Chang, M. Ho, and L. Morlock**, “Antibiotic Prescribing by Ambulatory Care Physicians for Adults with Nasopharyngitis, URIs, and Acute Bronchitis in Taiwan: a Multi-Level Modeling Approach,” *Family Practice*, April 2005, *22* (2), 160–167.
- Klevens, R. M., M. A. Morrison, J. Nadle, S. Petit, K. Gershman, S. Ray, L. H. Harrison, R. Lynfield, G. Dumyati, J. M. Townes, A. S. Craig, E. R. Zell, G. E. Fosheim, L. K. McDougal, R. B. Carey, S. K. Fridkin, and ABCs MSRA Investigators**, “Invasive Methicillin-Resistant *Staphylococcus aureus* Infections in the United States,” *Journal of the American Medical Association*, October 2007, *298* (15), 1763–1771.

- Lauderdale, Tsai-Ling, L. Clifford McDonald, Yih-Ru Shiau, Pei-Chen Chen, Hui-Ying Wang, Jui-Fen Lai, Monto Ho, and TSAR Participating Hospitals**, “The Status of Antimicrobial Resistance in Taiwan Among Gram-Negative Pathogens: The Taiwan Surveillance of Antimicrobial Resistance (TSAR) Program, 2000,” *Diagnostic Microbiology and Infectious Disease*, 2004, 48, 211–219,.
- Lautenbach, E., J. B. Patel, W. B. Bilker, P. H. Edelstein, and N. O. Fishman**, “Extended-Spectrum β -Lactamase-Producing *Escherichia coli* and *Klebsiella pneumoniae*: Risk Factors for Infection and Impact of Resistance on Outcomes,” *Clinical Infectious Diseases*, April 2001, 32 (8), 1162–1171.
- Laxminarayan, Ramanan and Gardner M. Brown**, “Economics of Antibiotic Resistance: a Theory of Optimal Use,” *Journal of Environmental Economics and Management*, September 2001, 42 (2).
- Lu, Jui-Fen Rachel and William C. Hsiao**, “Does Universal Health Insurance Make Health Care Unaffordable?,” *Health Affairs*, May/June 2003, 22 (3), 77–88.
- McDonald, L. Clifford, Tsai-Ling Lauderdale, Yih-Ru Shiau, Pei-Chen Chen, Jui-Fen Lai, Hui-Ying Wang, Monto Ho, and TSAR Participating Hospitals**, “The Status of Antimicrobial Resistance in Taiwan Among Gram-Positive Pathogens: the Taiwan Surveillance of Antibiotic Resistance (TSAR) Programme, 2000,” *International Journal of Antimicrobial Agents*, 2004, 23, 362–370.
- McFadden, Daniel**, “Conditional Logit Analysis of Qualitative Choice Behavior,” in Paul Zarembka, ed., *Frontiers in Econometrics*, New York: Academic Press, 1974, pp. 105–142.
- McGeer, Allison and Donald Low**, “Is Resistance Futile?,” *Nature Medicine*, April 2003, 9 (4), 390–392.
- Propper, Carol, Simon Burgess, and Katherine Green**, “Does Competition Among Hospitals Improve the Quality of Care? Hospital Death Rates and the NHS Internal Market,” *Journal of Public Economics*, 2004, 88, 1247–1272.
- Reese, Richard E. and Robert F. Betts, eds**, *A Practical Approach to Infectious Diseases*, Little, Brown and Company, 1996.
- Robinson, James C. and Harold S. Luft**, “The Impact of Hospital Market Structure on Patient Volume, Average Length of Stay and the Cost of Care,” *Journal of Health Economics*, December 1985, 4 (4), 333–356.
- Seppala, H., T. Klaukka, J. Vuopio-Varkila, A. Muotiala, H. Helenius, K. Lager, and P. Huovinen**, “The Effect of Changes in the Consumption of Macrolide Antibiotics on Erythromycin Resistance in Group A Streptococci in Finland,” *New England Journal of Medicine*, August 1997, 337 (7), 441–446.

- Spellberg, B., J. H. Powers, E. P. Brass, L. G. Miller, and J. E. Edwards**, “Trends in Antimicrobial Drug Development: Implications for the Future,” *Clinical Infectious Diseases*, May 2004, *38*, 1279–86.
- Spence, A. Michael**, “Monopoly, Quality, and Regulation,” *Bell Journal of Economics*, 1975, *6* (2), 417–429.
- Stewart, F. M., R. Antia, B. R. Levin, M. Lipsitch, and J. E. Mittler**, “The Population Genetics of Antibiotic Resistance II: Analytic Theory for Sustained Populations of Bacteria in a Community of Hosts,” *Theoretical Population Biology*, 1998, *53*, 152–165.
- Tirole, Jean**, *The Theory of Industrial Organization*, MIT Press, 1988.
- Van Der Meer, Jos W. M. and Bart Jan Kullberg**, “Defects in Host Defense Mechanisms,” in Robert H. Rubin and Lowell S. Young, eds., *Clinical Approach to Infection in the Compromised Host*, Kluwer Academic, 2002. Ch. 2.

Table 1: Summary Statistics by Market Concentration Quartile

Quartile (HHI)	(1)	(2)	(3)	(4)
HHI	0.06 (0.00)	0.15 (0.00)	0.30 (0.00)	0.68 (0.00)
Population	102,482 (1704)	66,218 (1268)	53,913 (1089)	26,340 (706)
Population density	135 (7)	119 (7)	131 (8)	25 (3)
Number of hospitals	2.52 (0.06)	1.94 (0.05)	1.49 (0.04)	0.71 (0.02)
Number of clinics	78.5 (1.49)	50.3 (1.28)	38.7 (1.08)	14.1 (0.56)
Physicians per hospital	37.62 (0.64)	77.23 (1.58)	146.51 (3.71)	270.56 (13.37)
Physicians per clinic	2.19 (0.00)	2.12 (0.01)	2.25 (0.01)	2.48 (0.02)
Number of physicians	266.3 (6.53)	249.9 (7.82)	303.9 (10.09)	215.4 (10.74)
Age of physician	44.93 (0.01)	44.98 (0.01)	44.23 (0.01)	43.24 (0.01)
Age of patient	35.18 (0.02)	37.30 (0.02)	39.67 (0.02)	40.98 (0.03)

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 (1.28)	-3.67 (1.31)	-2.02 (1.12)	-3.71 (1.02)	-0.77 (0.27)	-0.54 (0.23)	-0.58 (0.17)	-0.74 (0.18)
Firm size	-0.0052 (0.0018)	-0.0037 (0.0011)	0.0001 (0.0003)	-0.0030 (0.0012)	-0.0010 (0.0003)	-0.0007 (0.0002)	0.0002 (0.0000)	-0.0005 (0.0002)
Year-quarter effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Physician fixed effects	No	No	Yes	Yes	No	No	Yes	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

Outcome:	Antibiotics prescribed				Antibiotics share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HHI pre-regulation	-8.47 (1.53)	-7.86 (1.51)	-5.43 (1.33)	-7.49 (1.16)	-1.71 (0.33)	-1.45 (0.28)	-1.41 (0.19)	-1.61 (0.22)
HHI post-regulation	-0.31 (1.27)	0.25 (1.08)	1.14 (1.21)	-0.04 (0.98)	0.03 (0.29)	0.26 (0.18)	0.15 (0.21)	0.07 (0.15)
Firm size	-0.0054 (0.0018)	-0.0039 (0.0011)	-0.0004 (0.0003)	-0.0033 (0.0012)	-0.0010 (0.0003)	-0.0007 (0.0002)	0.0001 (0.0000)	-0.0005 (0.0002)
Year-quarter effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Physician fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
F statistic: HHI pre=HHI post	31.13 0.00	40.65 0.00	18.98 0.00	33.24 0.00	31.73 0.00	46.62 0.00	35.98 0.00	53.61 0.00
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.

"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.

"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

Outcome:	Antibiotics prescribed				Antibiotics share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HHI: age 0-9	-1.62 (1.80)	-2.01 (2.23)	-1.68 (3.96)	-0.38 (2.96)	0.25 (0.36)	0.42 (0.32)	-0.48 (0.63)	0.14 (0.44)
HHI: age 10-59	-5.22 (1.28)	-5.37 (1.32)	-5.73 (1.14)	-5.73 (1.07)	-0.98 (0.30)	-0.91 (0.25)	-1.32 (0.19)	-1.10 (0.22)
HHI: age 60+	0.57 (1.18)	-0.95 (1.12)	-1.43 (1.70)	-1.77 (1.41)	0.11 (0.23)	-0.26 (0.20)	-0.63 (0.36)	-0.57 (0.30)
Firm size	-0.0044 (0.0014)	-0.0040 (0.0012)	-0.0015 (0.0011)	-0.0033 (0.0013)	-0.0008 (0.0002)	-0.0007 (0.0002)	-0.0002 (0.0002)	-0.0005 (0.0002)
Year-quarter-group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Physician fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
F statistic: HHI equal by age	33.25 (0.00)	29.64 (0.00)	13.02 (0.00)	32.88 (0.00)	20.57 (0.00)	20.08 (0.00)	7.38 (0.00)	27184 (0.00)
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	0.050	0.129	0.224	0.241	0.030	0.115	0.187	0.215

Note: Heteroskedasticity-robust standard errors appear in parentheses. Standard errors are clustered by township. Coefficients and standard errors are multiplied by 100.

"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 5: Regressions of Antibiotic Resistance on Drug Age

Outcome: Model:	Resistance	
	OLS	Logit
	(1)	(2)
Drug Age	0.010 (0.002)	0.050 (0.010)
Constant	-0.010 (0.065)	-2.397 (0.426)
Sample size	117,391	117,391
R squared	0.095	0.077

Note: Standard errors are clustered by drug and are robust to heteroskedasticity.
 Included drugs: gentamycin, tobramycin, cefatrizine, cefazolin, ceftriaxone, cephalothin, cefuroxime, cefotaxime, trimethoprim, clindamycin, erythromycin, ampicillin, oxacillin, penicillin, piperacillin, ticarcillin, chloramphenicol, ciprofloxacin, levofloxacin, nalidixic acid, tetracycline.

Table 6: Social Costs Due to an Increase in Competition on One Standard Deviation

Estimate:	Baseline	Aggressive	Conservative
	(1)	(2)	(3)
Additional antibiotics purchases	94.3 (0.02)	94.3 (0.02)	94.3 (0.02)
Treatment of resistant infections	1,269.0 (0.32)	4,822.7 (1.22)	232.4 (0.06)
Total	1,363.3 (0.35)	4,917.0 (1.25)	326.7 (0.08)

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

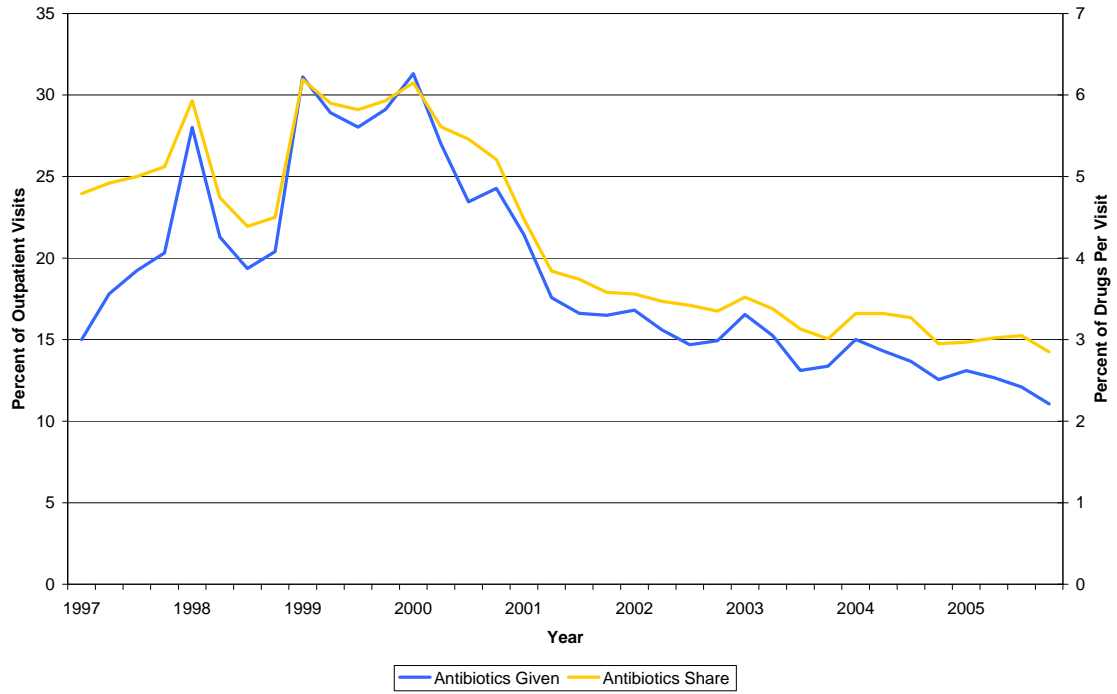


Figure 2A: Median Market Concentration Over Time

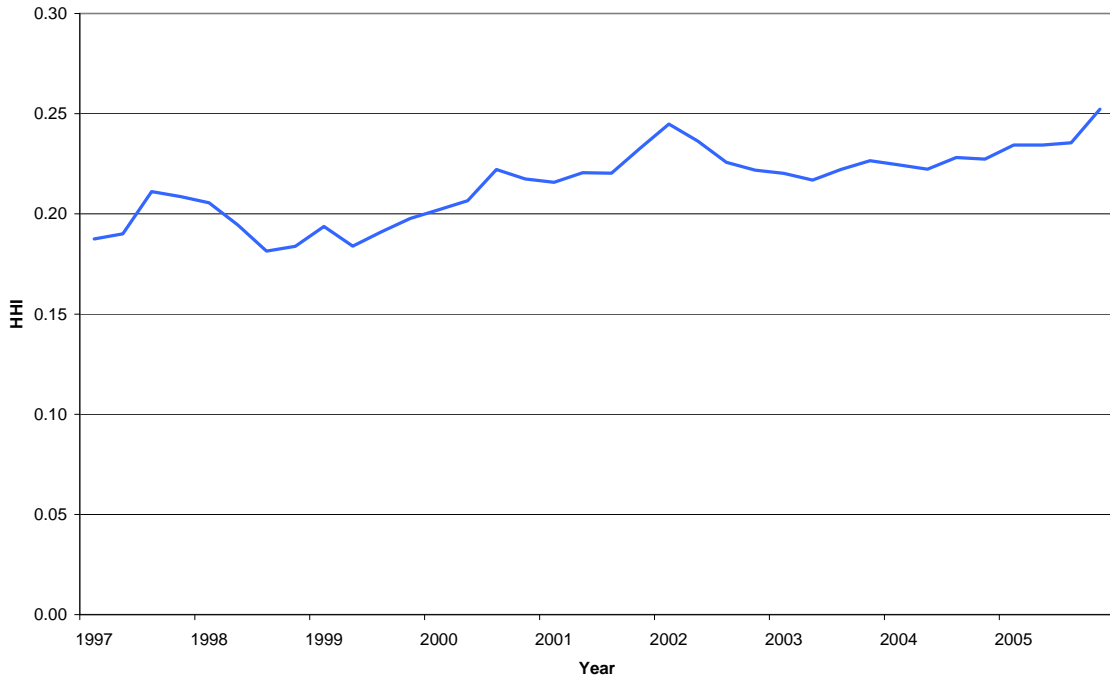


Figure 2B: Number of Firms: 1997-2005

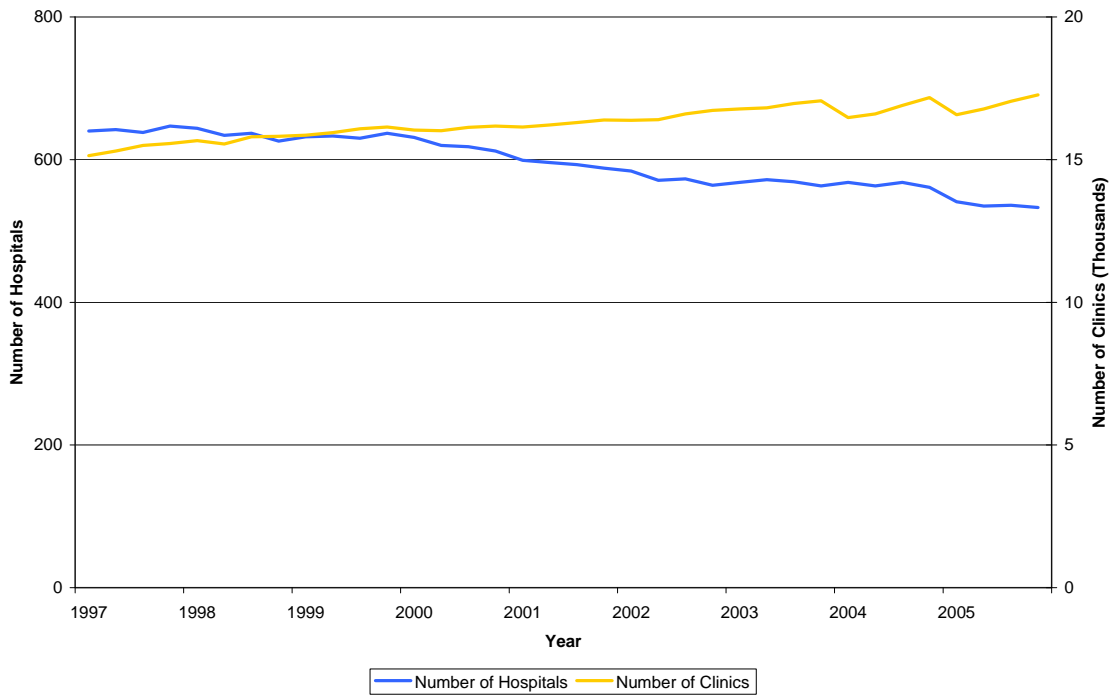


Figure 2C: Number of Providers Per Firm: 1997-2005

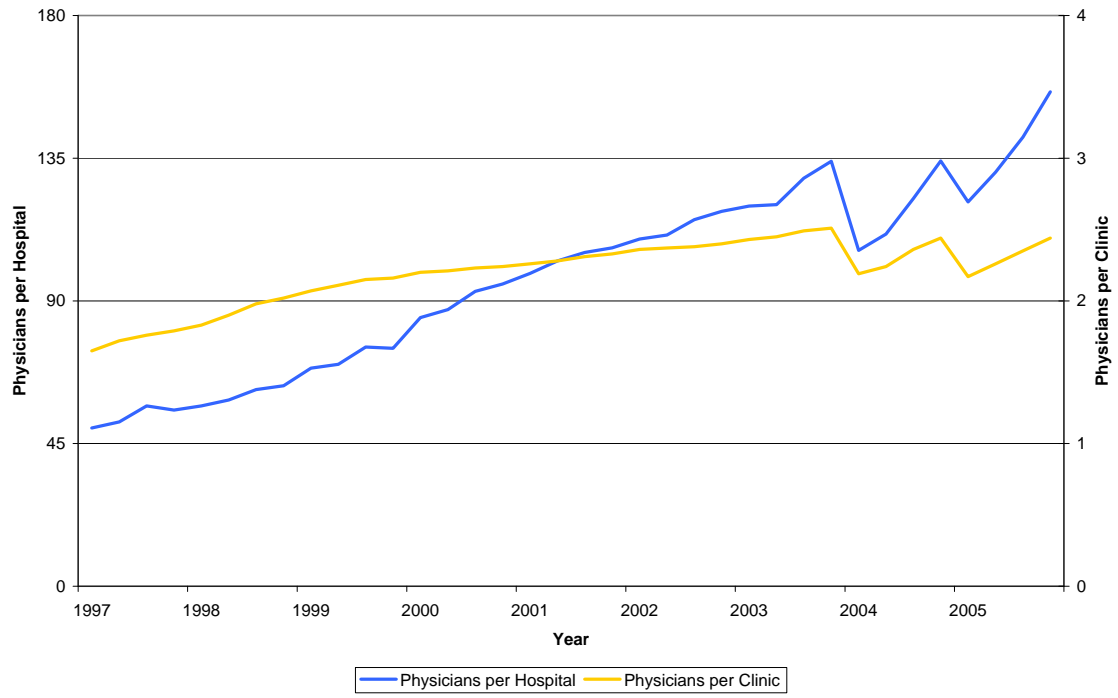


Figure 3A: Effect of Market Concentration on "Antibiotics Prescribed": 1997-2005



Figure 3B: Effect of Market Concentration on "Antibiotics Share": 1997-2005



Figure 4: Quarterly Volume of Outpatient Visits: Total and 4-Quarter Moving Average

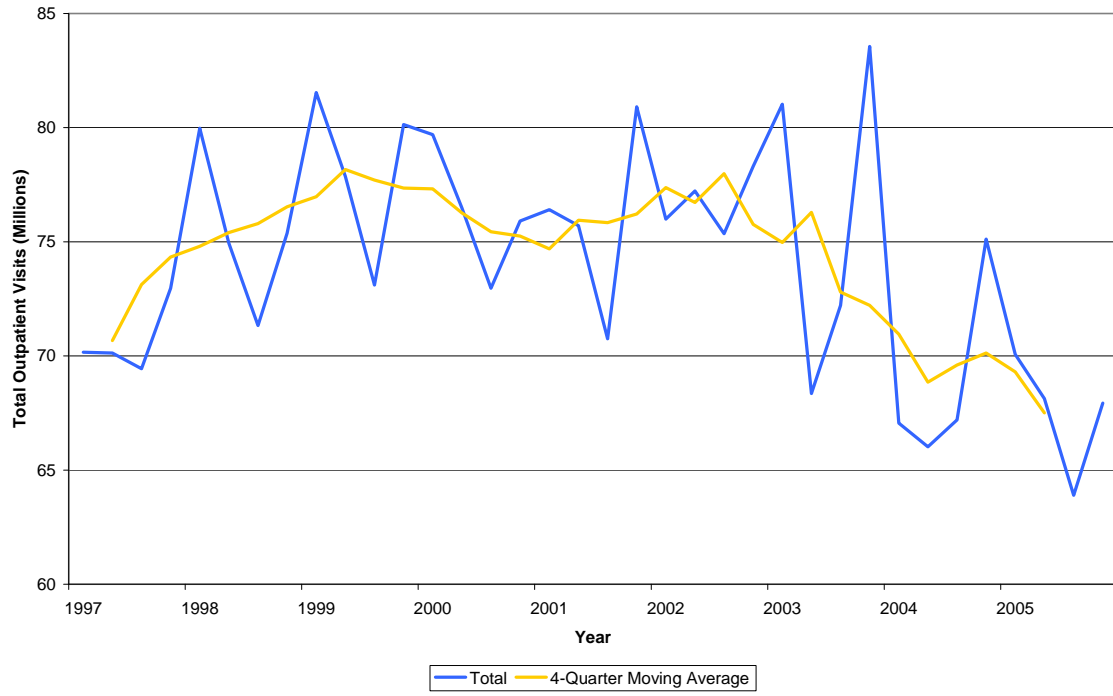


Figure 5: Monthly Antibiotic Use Per Capita by Patient Age Cohort

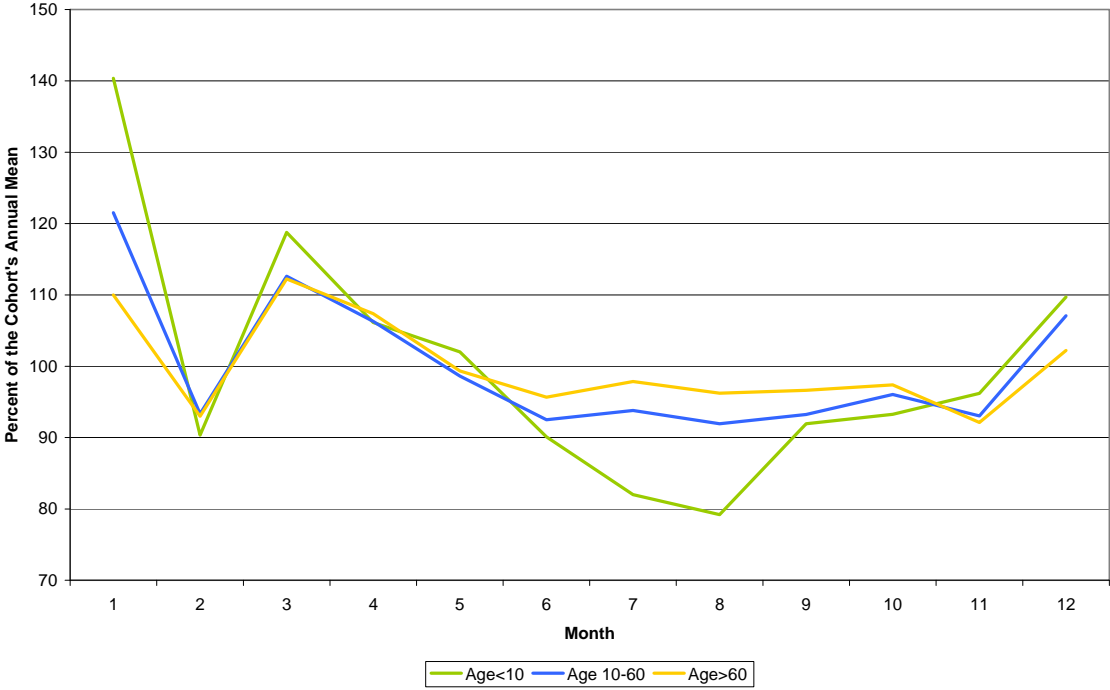


Figure 6: Effect of Market Concentration on Antibiotic Use by Patient Age

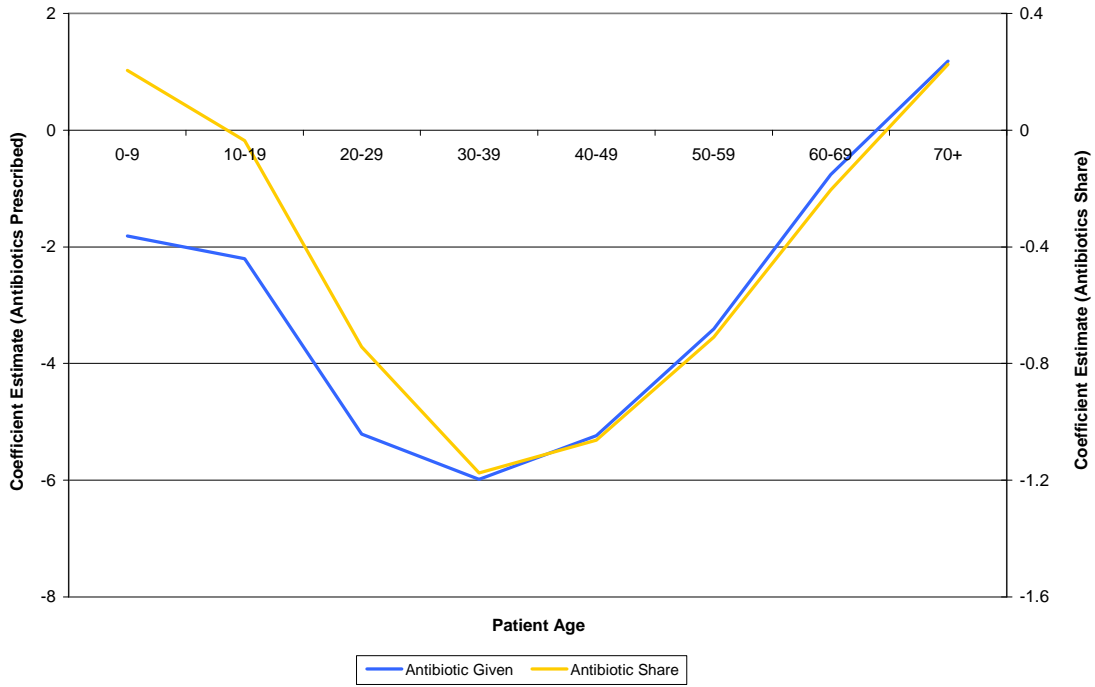


Figure 7A: The Estimated Path of Antibiotic Resistance and the Path Implied by an Increase in Competition of One Standard Deviation

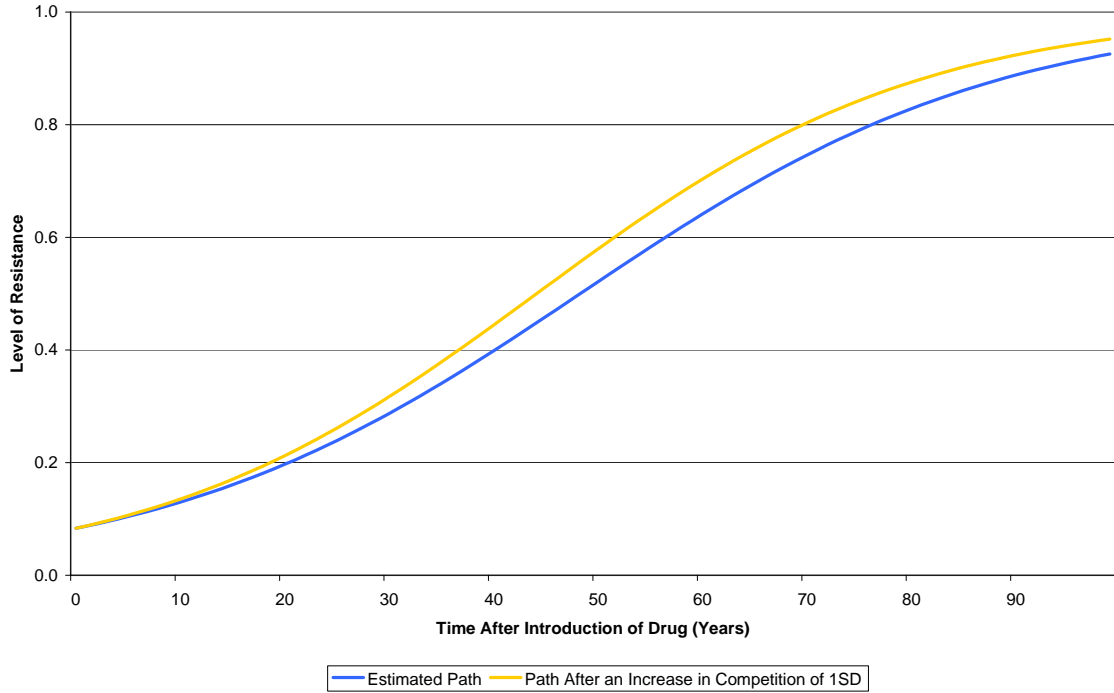


Figure 7B: Drug Ages and Levels of Resistance in 1998

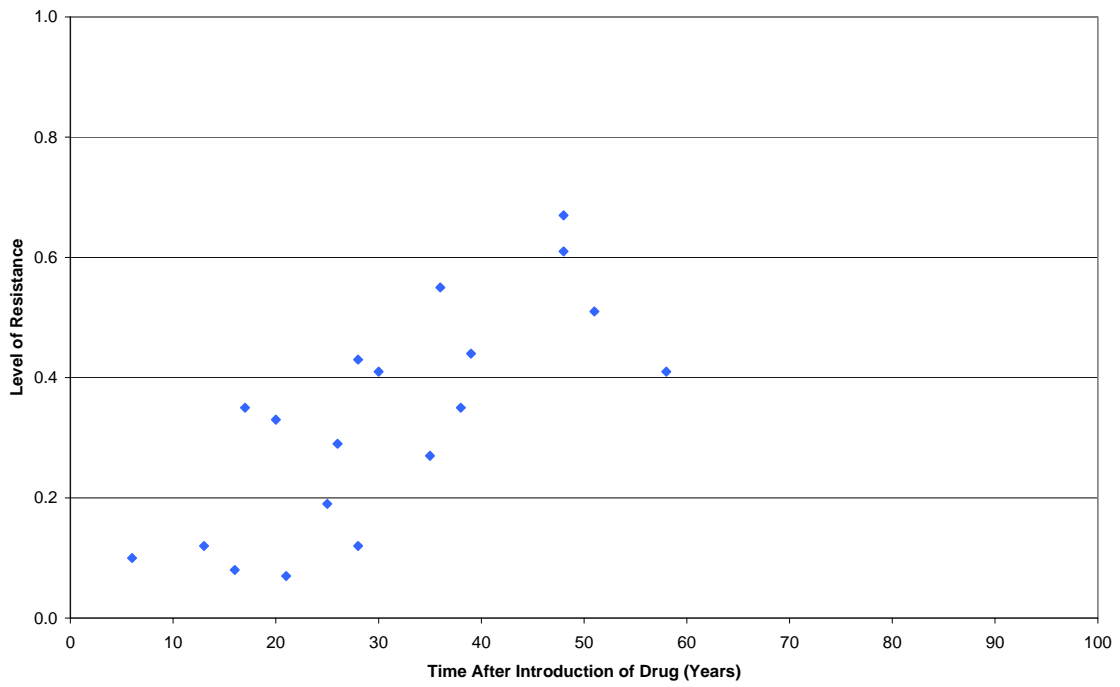


Figure 8: Percentage Increase in Resistance Due to an Increase in Competition of One
Standard Deviation: Estimates Using Different Elasticities

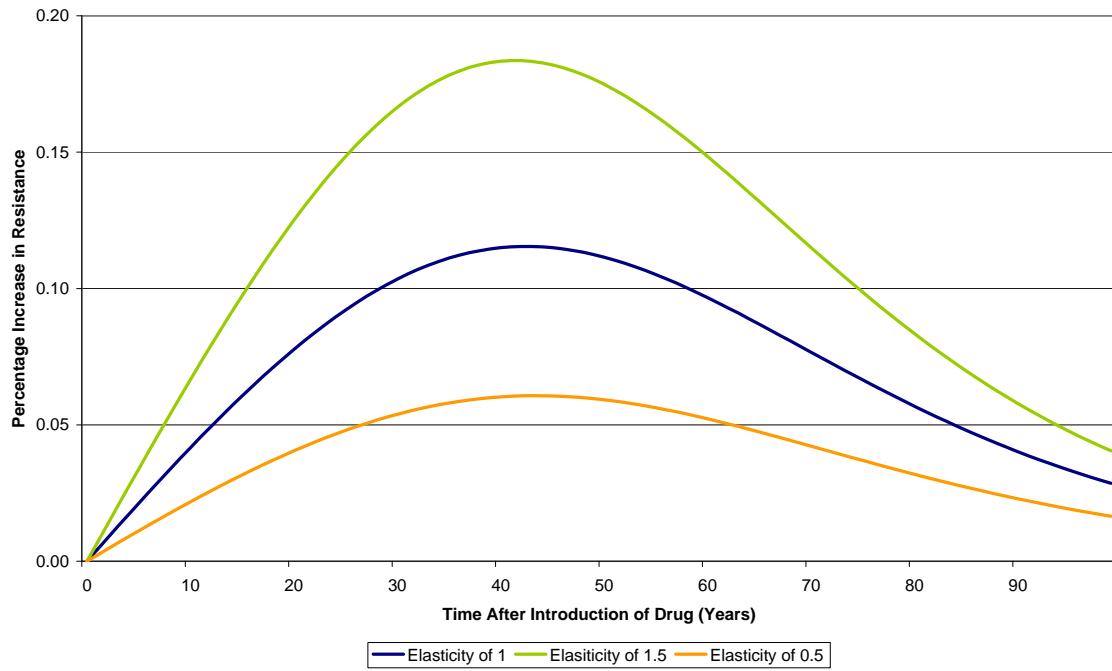


Figure 9: Additional Annual Costs of an Increase in Competition of One Standard Deviation

