NATIONAL HEALTH INSURANCE AND TECHNOLOGY ADOPTION: EVIDENCE FROM TAIWAN

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Generous health-insurance coverage may encourage hospitals to acquire and employ more advanced medical technologies. The authors examine the effects of Taiwan's 1995 implementation of National Health Insurance on technology adoption, ownership, and use by comparing changes in adoption, ownership, and use rates by private hospitals with changes by public nonteaching and public teaching hospitals. Using random-effect panel probit and tobit models, the article finds strong empirical evidence that third-party payment increases the probability of technology adoption, ownership, and use. (*JEL* H4, I)

I. INTRODUCTION

Persistent growth of health-care expenditures, extensive use of third-party payment mechanisms, and rapid technological progress have been prominent features of the medical-care sector over recent decades (Weisbrod, 1991). A more generous health-insurance system results in higher expected health-care utilization due to moral hazard and thus higher expected returns for health-care providers. This mechanism motivates the growth of biomedical research and encourages hospitals to adopt and use expensive medical technologies. Reciprocally, the dramatic progress of medical technology changes the demand for health insurance. Given that technological change is predominantly cost-increasing, people respond to higher levels of uncertainty about medical costs by demanding more insurance.[1]

Despite these conceptually well-established causalities, direct empirical evidence about the relationship between health insurance and changes in medical technology is limited. The purpose of this study is to provide such evidence. The authors examine the effects of Taiwan's 1995 implementation of National Health Insurance (NHI) on technology adoption, ownership, and utilization by hospitals. NHI provides coverage to nearly all Taiwanese residents. It replaced a set of worker insurance programs that typically did not cover workers' dependents. In the first three years after implementation, the insured population increased by 70%.

The adoption of NHI provides an opportunity to test the effects of insurance on demand for medical technology that is relatively uncontaminated by reverse causality. First, although rising health-care costs provided impetus for development of NHI, the program was adopted nationwide, replacing previous insurance programs, and so the change in coverage is

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1. The demand for insurance is likely to depend on whether technological change is cost-increasing or cost-decreasing. Organ-transplant technology appears to be cost-increasing, as it is now possible to spend vast amounts on effective heart and lung transplants for people who in the past would have died with little health-care expenditure. In contrast, improvements in the control of many infectious diseases are cost-decreasing. Reduced uncertainty about spending on these illnesses should dampen demand for health insurance.

ABBREVIATIONS

CT: Computerized Tomography
NHI: National Health Insurance
NMR: Nuclear Magnetic Resonance

Contemporary Economic Policy
(ISSN 1074-3529)
Vol. 22, No. 1, January 2004, 26–38
DOI: 10.1093/cep/byh003

exogenous to any given hospital. Second, the timing of adoption was primarily motivated by political factors rather than by developments in the health-care sector. NHI was proposed in 1984 and was initially scheduled for implementation in 2000. During the chaotic political situation of the late 1980s and 1990s, the political party in power (the Kuomingtung) attempted to consolidate its position by advancing the implementation of NHI to 1995. These factors suggest that the 1995 implementation of NHI may be viewed as exogenous to the adoption, ownership, and utilization of medical technologies by hospitals, and so one may identify its effect on technology adoption without contamination by the reciprocal effect of technology adoption on health-insurance reform.

This article employs difference-in-differences estimates to control for systematic structural changes in health-care-technology use. The authors use private hospitals as the treatment group, and public teaching and public nonteaching hospitals as control groups. The authors anticipate that private hospitals are the most responsive to changes in financial conditions associated with implementation of NHI and expect that public nonteaching hospitals responded more slowly than private hospitals to adoption of NHI. These hospitals are subsidized by the government and have weaker financial incentives to respond to the policy change. Moreover, managerial decisions at these hospitals often entail a long bureaucratic process. The authors also anticipate that public teaching hospitals responded more slowly because these hospitals' technology decisions are affected by their teaching mission as well as by financial factors. Prior to the reform, public teaching hospitals had acquired and used technologies more extensively than private and public nonteaching hospitals. By exploiting the variation in responses to the NHI reform, the authors attempt to identify its effect on technology adoption, ownership, and utilization for private hospitals.

This article employs a random-effect panel probit to estimate the probabilities of adoption and ownership of specific technologies and a panel tobit to estimate the use of these technologies. After controlling for hospital characteristics and market competition, the authors find that the implementation of NHI significantly increased the probability of technology adoption and ownership and the use of technologies for private hospitals. These results are robust to different specifications. Because the authors anticipate that the more generous coverage provided by NHI increased technology use in all hospitals, the estimates of the differential effects of NHI on private hospitals may be considered lower bound estimates of the total effects of NHI on technology adoption, ownership, and use in private hospitals.

The article proceeds as follows: section II provides a brief review of the related literature and some background on Taiwan's NHI. Section III describes the identification strategy. Section IV presents the data and descriptive statistics. Section V reports the estimation results, and section III concludes.

II. BACKGROUND

A. NHI in Taiwan

Taiwan implemented NHI in March 1995. The objective of the reform was to provide equal access to adequate health care at a socially affordable cost. Prior to implementation of NHI, there were three major health-insurance programs sponsored by the government—Labor Insurance, Government Employees' Insurance, and Farmer Health Insurance. The working population was almost entirely covered by these three programs. There was virtually no private health insurance. Those without coverage were mostly children, the elderly, unemployed workers, and housewives. The NHI is a single-payer insurance program that consolidated the three social insurance programs and extended coverage to the uninsured population. The implementation of NHI increased the insured fraction of the population from 57% in 1994 to 97% in 1998.

The reform process was heavily influenced by political factors (Chiang, 1997; Hu and Hung, 2002). In 1984, the Council for Economic Planning and Development recommended an NHI scheme to be phased in by 2000. In 1986, the premier declared the objective of "health insurance for all by the year 2000" in his statement to the Legislative Yuan. However, with the rapid growth of political participation and the growth of the opposing Democratic Progressive Party in the 1980s, in February 1989 the premier strategically announced the new target year for implementing an NHI scheme to be 1995. Foreseeing an election of Legislative Yuan representatives in December 1995 and a presidential election in March 1996, the Kuomingtung mobilized its legislators to pass the NHI Law in July 1994. NHI was fully implemented by March 1995 so that the chaos resulting from implementation might vanish prior to the elections. Thus, although the development of universal health insurance was motivated by concerns about health, the driving force behind the timing of implementation of NHI was political.[2]

Before implementation of NHI, the three social insurance programs provided a similar range of benefits, including outpatient visits, inpatient care, and prescription drugs. Approximately 85% of hospitals and 70% of clinics contracted with the social insurance programs in 1994. Two years later, after implementation of NHI, the proportion of contracting institutions increased to 97% of hospitals and 90% of clinics. NHI coverage also extends to severe illnesses and home health care (Cheng and Chiang, 1997). For outpatient visits, the out-of-pocket expenditure ranges from NT$50 to NT$150.[3] For hospitalization expenses, the copayment ranges from 5% to 30%, depending on length of stay. In the case of major illness and injury, the copayment is waived. Because consumers face a low copayment, moral hazard is likely to increase health-care utilization.

The major payment method under NHI is fee-for-service. This system provides health-care providers an incentive to generate a high volume of services to increase their revenue. Physicians have incentives to provide more extensive or more expensive care. NHI does not rely on nonphysician gatekeepers to limit access to medical care. Under the NHI regime, because patients are free to select a hospital with almost no financial constraint, hospitals face inelastic demand for medical care services and have little incentive to engage in price competition. Hospitals may be more likely to engage in nonprice competition, competing for patients by providing the latest technology and excessive care.

Consistent with theoretical expectations, health-care costs have increased rapidly under NHI. According to statistics from the Bureau of NHI, health-care expenditures increased at a 19.6% annual rate from 1996 to 1997, exceeding the 15.3% annual rate from 1990 to 1994 (Chiang, 1997). Hu and Hsieh (1999) disaggregated the factors contributing to the increase in health-care expenditures. They found that outpatient expenditures increased 41% and inpatient expenditures increased only 21% from 1995 to 1998.[4] Within outpatient expenditures, the increases were attributed primarily to the increase in quantity of patients treated. In contrast, only 35% of the increase in inpatient expenditures was due to the increase in quantity, whereas 65% was due to the increase in cost per admission or cost per inpatient day. The limited effect of quantity change on inpatient expenditures is similar to Newhouse's (1988) finding that inflation due to insurance-induced demand increases accounted for only a minority portion of the rise in expenditures from 1950 to 1984 in the United States.

The increase in cost per admission highlights a substantial role for technological change, and there is consensus among health economists that technological change is a primary factor in rising per capita health-care expenditures (Fuchs, 1996). Thus insurance may contribute to medical-care inflation not only through its direct role in boosting demand but also through its effect on technological diffusion. Health insurance may induce hospitals to adopt more advanced medical technologies, which are cost-increasing (Godderis, 1984). In addition, the third-party payment system encourages physicians to use these expensive technologies. Whether the benefits of the new technologies exceed their costs is uncertain.

B. *Prior Literature*

Increased moral hazard resulting from third-party payment and advances in medical technology have been recognized as driving forces behind the rapid growth of health-care expenditures. Weisbrod (1991) notes that the demand for health insurance and technological diffusion are interdependent. On the one hand, most medical technology innovations are cost-increasing, and these advanced medical technologies increase unexpected medical-care

2. Chiang (1997) provides a more detailed description of the reform process, and Chou and Staiger (2001) describe the health insurance systems that preceded NHI.

3. The 1995 exchange rate was NT$27.26 = US$1.

4. These growth rates are in nominal terms. As the general price level increased at an average annual rate of only 1.6% between 1995 and 1998, the increases in real medical care expenditures is substantial.

expenses for treatments that were previously unavailable. Consequently, the importance of risk pooling is enhanced. On the other hand, expanded health-care insurance relaxes the financial constraints faced by health-care providers and fosters the development and adoption of advanced medical technologies. More generous health insurance may also encourage physicians to change practice patterns in a way that encourages greater use of new technologies.

Previous studies have found that the rate of technology diffusion is associated with changes in health insurance. Sloan et al. (1986) found that a high share of commercial coverage, which typically pays the highest proportion of hospital charges, leads to greater diffusion; conversely, high shares of public and self-coverage are associated with slow diffusion. Mandatory rate-setting programs, which reduce hospitals' cash reserves, have a negative impact on technology diffusion. Several studies have also examined the influence of the prospective-payment system on the diffusion of new technologies (Romeo et al., 1984; Lee and Waldman, 1985; Sloan et al., 1988).

Recent empirical findings suggest that managed care in the United States may slow the growth of medical technology. For example, Hill and Wolfe (1997) found that the adoption of nuclear magnetic resonance (NMR) imaging and lithotripsy decreased as managed care grew. Cutler and McClellan (1996) suggested that increases in health maintenance organization market shares are associated with decreases in the availability of angioplasty. Baker (2001) reported similar findings for NMR imaging. Reciprocally, a theoretical paper (Baumgardner, 1991) also showed that the advancing capabilities of medicine over time may make managed care more attractive because its management constraint will reduce moral hazard.

Although economic theory suggests that increases in third-party coverage fuel the inflow of resources to the health-care sector and encourage adoption of expensive technologies, empirical evidence on the role of third-party payment in technology adoption is limited. One reason for the lack of empirical evidence is that it is difficult to disentangle directions of causality in the interdependent evolution of hospital technology, insurance coverage, and expenditures. The growth of hospital expenses may be a response to rapid technological diffusion, but the growth of third-party payment systems may also be a response to the development of expensive technologies that are perceived as worthwhile and create demand for greater insurance coverage to finance their use.

This study offers several advantages for empirically examining the effects of third-party payment on technology diffusion. The authors evaluate the link between third-party payment and technology adoption by comparing technology-adoption rates before and after NHI. Because this variation is created by law, the article avoids selection bias associated with hospitals' choice of funding sources. Previous studies use either the share of hospital revenue by payment source (Sloan et al., 1988) or the share of uninsured in the geographic area (Cutler and McClellan, 1996) to represent the generosity of health-insurance coverage and thus suffer from possible selection bias. Hospitals that intend to use expensive technologies may admit more private-pay patients or locate in an area with more generous health-insurance coverage.

III. IDENTIFICATION STRATEGY

The current data consist of a number of repeated cross-sections over a relatively small number of time periods. Though repeated cross-sections allow one to use before-and-after analysis, this strategy captures not only the NHI reform effect but also other contemporary shocks.[5] To control for the presence of common shocks, these authors require some cross-sectional variation. The difference-in-differences estimates rely on comparing otherwise similar groups of hospitals that are anticipated to have been affected in different ways by the reform. The idea is that the outcome change for the control group captures the effect of any common shock, whereas the treatment group's outcome change reflects the common shock plus the impact of the intervention.

Private hospitals comprise the treatment group. The authors use two control groups: public nonteaching hospitals and public teaching hospitals. Public nonteaching hospitals are subsidized by the government and are less affected by the dynamics of the market,

5. See Meyer (1995) for discussion of before-and-after and difference-in-differences analyses.

as subsidies may be changed to offset any change in market revenues. Because public nonteaching hospitals are not able to claim the residuals, they have weaker financial incentive to adjust their behaviors to the change of policy. Moreover, it is generally believed that managerial decisions at these hospitals are made through a long bureaucratic process. The authors expect that NHI has a smaller effect on technology adoption and utilization for these hospitals. In contrast, public teaching hospitals (the second control group) usually have more research and development activities, have more information on new technologies, and have the obligation to train personnel in the use of new techniques. Thus many public teaching hospitals had already adopted the technologies studied herein before the NHI reform and had used them more extensively than other hospitals. Therefore, the effects of NHI on public teaching hospitals' adoption and use of new technologies should be limited. An advantage of using two control groups is that if one finds similar results, one can be more confident of estimating an actual effect of NHI reform and not an effect of other contemporaneous changes or trend differences between treatment and control groups.

IV. DATA

The data were obtained from the annual Medical Facility and Service Volume Survey conducted by the Taiwan Department of Health from 1993 to 1998. These data provide detailed information on output, hospital characteristics (i.e., ownership, number of beds, number of specialties), and number of physicians and medical staff for all medical facilities in Taiwan. Of particular interest is the information on whether a hospital has any expensive or dangerous medical devices, including, a computerized tomography (CT) scanner, radiation isotope therapeutic equipment, radiation isotope diagnostic equipment, linear acceleration equipment, NMR tomography, and shock wave lithotripsy equipment. These six annual samples are merged by hospital to construct a panel data set.

The original sample sizes are 810 in 1993, 828 in 1994, 787 in 1995, 773 in 1996, 750 in 1997, and 719 in 1998. After deleting observations with missing values, the estimation sample contains 683 hospitals in 1993, 715 in 1994, 676 in 1995, 640 in 1996, 603 in 1997, and 568 in 1998.[6] Pooling all six years produces a panel including 3321 observations (hospital-years) for private hospitals, 345 for public nonteaching hospitals, and 219 for public teaching hospitals.[7] Finally, if considering only those hospitals which survived all six years, the balanced panel includes 3048 observations (508 hospitals).

Table 1 presents summary statistics for the treatment and control groups before and after implementation of NHI. Comparing private and public nonteaching hospitals before NHI (columns 1 and 3) reveals some differences. Public nonteaching hospitals tend to be larger (49.2% having more than 300 beds, versus 7.1%), to have a larger medical staff (4528 versus 1329), and more specialties (10 versus 4). Public nonteaching hospitals are more likely to be located in a less competitive market, indicated by a larger Herfindahl index.[8] Public teaching hospitals are even more different from private hospitals. Public teaching hospitals are much bigger, with more medical staff and specialties. A comparison of hospital characteristics after NHI (columns 2 and 4) also suggests systematic differences between the groups. These summary statistics suggest that any raw differences in technology adoption between the treatment and control groups must be interpreted with caution, because the differences could reflect nonreform shocks that affect hospitals with some characteristics differently from hospitals with other characteristics.

There are no statistically significant changes in public nonteaching or teaching hospitals' characteristics after the NHI reform (columns 3 and 4 and columns 5 and 6 in Table 1). Private hospitals tend to become larger, have more medical staff, have more specialties, and be located in a less competitive market after the reform. Ideally, the composition of both experimental and control groups remains

6. Observations with missing values are due to hospital closure. Those hospitals are more likely to be small, private, nonteaching hospitals. A formal Hausman test for selectivity does not suggest the presence of attrition bias due to hospital closures. Results are available on request.

7. The 255 private teaching hospitals are included in the treatment group.

8. The Herfindahl index is obtained by summing the squared market shares of all hospitals in a geographical market. The authors define the geographic market using the medical care regions reported by the ROC Department of Health (1999) and define market share as the proportion of inpatient days.

TABLE 1
Summary Statistics

	Treatment Group		Control Group I		Control Group II	
	Private Hospitals		Public Nonteaching Hospitals		Public Teaching Hosp.	
	(1) Before NHI	(2) After NHI	(3) Before NHI	(4) After NHI	(5) Before NHI	(6) After NHI
Hospital characteristics						
0–30 beds	0.240	0.245	0.085	0.065	0.000	0.000
	(0.427)	(0.430)	(0.279)	(0.248)		
301–600 beds	0.046	0.050	0.356	0.375	0.255	0.230
	(0.210)	(0.219)	(0.480)	(0.486)	(0.438)	(0.423)
>600 beds	0.025	0.041[b]	0.136	0.155	0.226	0.212
	(0.155)	(0.197)	(0.343)	(0.363)	(0.420)	(0.411)
Number of medical staff (100s)	13.293	16.116[c]	45.282	42.810	120.557	107.027
	(43.281)	(53.377)	(50.117)	(45.471)	(202.072)	(199.689)
Number of specialties	4.173	4.746[a]	9.944	10.512	14.236	13.858
	(4.712)	(5.386)	(6.991)	(7.249)	(4.497)	(4.849)
Market structure						
Herfindahl index	0.144	0.174[a]	0.194	0.211	0.184	0.201
	(0.086)	(0.100)	(0.181)	(0.160)	(0.135)	(0.119)
Sample size	1791	1530	177	168	106	113

Notes: Significance levels are for test of difference in means before and after NHI within group. Standard deviations are in parentheses. Before NHI is 1993–95; After NHI is 1996–98.

[a]Statistically significant at the 1% level.

[b]Statistically significant at the 5% level.

[c]Statistically significant at the 10% level.

stable before and after the policy change, so that the individual hospital characteristics can be aggregated out. The limited changes in the characteristics of control-group hospitals suggest that selection effects are not likely to bias the estimates of the effect of NHI.

To further examine possible selection effects, the authors construct statistics that reflect the mix of patients served by a hospital and examine how these indicators of patient mix change after NHI (Table 2). The proportion of outpatient visits involving surgery remained quite stable in all hospital types, whereas the proportion of hospitalizations for surgery decreased after the reform in private and both types of public hospitals. The ratio of emergency-room visits to outpatient visits decreased slightly for private and public teaching hospitals and increased slightly for public nonteaching hospitals. The mix of acute-care, chronic-care, and special-care hospitalizations remained stable after the reform. Taken together, these results do not suggest significantly different changes in patient mix after NHI and support the conclusion that selection bias should be minimal.

V. EMPIRICAL RESULTS

The authors examine three measures of technology in hospitals: ownership, adoption, and use. Ownership is measured as a dummy variable, own_{it}, which is equal to one if hospital i owns the technology in year t and zero otherwise.[9] Adoption is the transition of ownership. The variable $adopt_{it}$ is equal to one if hospital i acquires the medical technology in year t and zero otherwise.[10] Technology utilization is measured by a variable use_{it}, which is a count of the number of patients who are treated with the technology at hospital i in year t.

A. Regression Results

The difference-in-differences estimates can be described in a regression framework. The

9. Information on hospital ownership of medical technology is unavailable for 1996-97; therefore, the authors define the dependent variable as one if the hospital used the technology at least once.

10. For example, if hospital i had the technology from 1993 to 1998, then $adopt_{it}$ is equal to zero in all years. If hospital i acquired the technology in 1995, then $adopt_{it}$ is equal to one in 1995 and zero in all other years.

TABLE 2
Patient Mix

	Treatment Group		Control Group I		Control Group II	
	Private Hospitals		Public Non-teaching Hosp.		Public Teaching Hosp.	
	Before NHI	After NHI	Before NHI	After NHI	Before NHI	After NHI
Proportion of outpatient visits having surgery	0.010 (0.057)	0.008 (0.076)	0.004 (0.005)	0.004 (0.004)	0.006 (0.005)	0.007 (0.006)
Proportion of hospitalizations having surgery	0.263 (0.847)	0.223[c] (0.279)	0.179 (0.314)	0.119[b] (0.170)	0.332 (0.224)	0.274[b] (0.141)
Ratio of ER visits to outpatient visits	0.050 (0.170)	0.043[c] (0.054)	0.049 (0.044)	0.053 (0.045)	0.071 (0.037)	0.069 (0.034)
Acute care patients as proportion of inpatient days	0.899 (0.209)	0.872 (0.232)	0.727 (0.344)	0.729 (0.330)	0.846 (0.184)	0.843 (0.159)
Chronic care patients as proportion of inpatient days	0.057 (0.214)	0.046 (0.190)	0.306 (0.396)	0.212 (0.338)	0.075 (0.190)	0.044 (0.124)
Special care patients as proportion of inpatient days	0.067 (0.142)	0.081 (0.153)	0.040 (0.063)	0.045 (0.063)	0.088 (0.070)	0.096 (0.072)

Notes: Significance levels are for test of difference in means before and after NHI within group. Standard deviations are in parentheses.

[a]Statistically significant at the 1% level.

[b]Statistically significant at the 5% level.

[c]Statistically significant at the 10% level.

authors consider the following random-effects panel probit model for the probability that hospital i owns a specified medical technology in period t:[11]

$$P(own_{it}=1) = \Phi(\beta_0 NHI_{it} + \beta_1 \mathrm{Private}_{it} + \beta_2 \mathrm{Private}_{it} \times NHI_{it} + \beta X_{it} + \alpha_i').$$

NHI_{it} is a dummy variable equal to one for any year from 1996 to 1998, and $\mathrm{Private}_{it}$ is a dummy for treatment group (one if private hospital, zero if public nonteaching or public teaching hospital). Thus β_0 reflects the average change in technology ownership for both treatment and control groups after the NHI reform, and β_1 captures the time-invariant difference between the treatment and control groups. The effect of NHI can be expressed as $\Delta^{NHI} = (\beta_0+\beta_2) - \beta_0 = \beta_2$. The coefficient β_2 estimates the lower bound of the NHI reform on technology ownership.[12] X_{it} is a vector that includes three dummy variables for number of beds (0–30, 301–600, over 600), number of specialties, number of medical staff, Herfindahl index, percentage of hospitals in the same geographic market with the technology, and year dummies.

The authors estimate the probability of technology adoption using a similar model but restrict the sample to hospitals that did not own the specific technology in the initial year of the sample (1993). Finally, the authors also use a random-effect panel tobit model to estimate the intensity of technology utilization because the dependent variables (the number of uses for each of the five technologies) are bounded by zero.[13] Only the estimates of β_2 are reported in the following tables.

11. The random-effects probit model assumes the hospital specific effects are independent of the explanatory variables and are randomly sampled from a univariate distribution. As discussed in Hsiao (1986), when the dependent variable is binary, under the fixed-effects specification, neither hospital specific effects nor coefficients of explanatory variables will be consistently estimated using a short period of panel data. Therefore, the authors use a random-effects model. The estimates are carried out using LIMDEP version 7.0. One can test whether our data are consistent with the random-effects model. If there is no discernible evidence of random effects in the data, the estimate of correlation coefficient of hospital specific effects will be negligible.

12. It is a lower bound because NHI is anticipated to increase technology adoption in the control groups, albeit at a slower rate.

13. Difference-in-differences estimates can also be obtained using limited dependent variable models. For example, Madrian (1994) studied the impact of

TABLE 3
Difference-in-Differences Estimates of the Effects of NHI on Technology Ownership and Adoption Probability and Intensive Use of Technology

	CT Scanner	Radiation Isotope Diagnostic Equipment	Linear Acceleration Equipment	NMR Tomography	Shock Wave Lithotripsy Equipment
Control group: public nonteaching hospitals					
Technology ownership probability ($N = 3666$)					
Private * NHI	0.962[a]	1.811[a]	2.344[a]	0.620	1.668[a]
	(0.367)	(0.347)	(0.786)	(0.542)	(0.329)
	[0.110]	[0.098]	[0.009]	[0.010]	[0.031]
Technology acquisition probability ($N = 2912$)					
Private * NHI	0.843[b]	2.286[a]	2.168[a]	1.311[a]	1.659[a]
	(0.350)	(0.305)	(0.680)	(0.497)	(0.377)
	[0.037]	[0.236]	[0.019]	[0.012]	[0.035]
Intensive use of technology ($N = 3666$)					
(Dependent variables/1000)					
Private * NHI	0.440[b]	14.917[a]	11.568[a]	1.152[a]	0.746[a]
	(0.207)	(2.637)	(4.242)	(0.322)	(0.100)
	[0.028]	[0.026]	[0.001]	[0.0001]	[0.0001]
Control group: public teaching hospitals					
Technology ownership probability ($N = 3540$)					
Private * NHI	0.217	3.401[a]	1.687	13.109[a]	1.601[a]
	(0.370)	(0.629)	(1.085)	(4.018)	(0.478)
	[0.022]	[0.183]	[0.009]	[0.080]	[0.026]
Technology acquisition probability ($N = 2809$)					
Private * NHI	0.698[b]	2.849[a]	2.034[a]	2.026	1.436[a]
	(0.333)	(0.782)	(0.610)	(1.349)	(0.336)
	[0.044]	[0.086]	[0.017]	[0.014]	[0.031]
Intensive use of technology ($N = 3540$)					
(Dependent Variables/1000)					
Private * NHI	2.360[a]	22.193[a]	1.397	0.519[b]	0.739[a]
	(0.138)	(2.943)	(2.779)	(0.233)	(0.156)
	[0.276]	[0.173]	[0.0001]	[0.00005]	[0.00007]

Notes: Standard errors are in parentheses. Marginal effects (at sample mean) are in brackets. Other explanatory variables include NHI dummy, a dummy for private hospital, three dummies for number of beds (0–30, 301–600, over 600), number of specialties, number of medical staff, Herfindahl index, percentage of hospitals in region with technology, and year dummies for 1994, 1995, 1997, and 1998.

[a]Statistically significant at the 1% level.

[b]Statistically significant at the 5% level.

The top portion of Table 3 presents results using public nonteaching hospitals as the control group. The difference-in-differences estimates of the effect of NHI reform on technology ownership are positive and statistically significant, except the one for NMR tomography. Moreover, the marginal effects (estimated at the mean of the independent variables) suggest that NHI increased the probability of owning CT scanners by 11%, radiation isotope diagnostic equipment by 9.8%, linear acceleration equipment by 0.9%, NMR tomography by 1.0%, and shock wave lithotripsy equipment by 3.1%.[14] NHI also increased the probability of acquiring CT scanners by 3.7%,

employer-provided health insurance on job mobility. For testing the extent of job lock, the difference-in-differences regression is estimated as a probit model. Gruber (2000) studied the impact of disability insurance on labor force participation in Canada. The difference-in-differences regression is estimated as a logistic model.

14. The authors also estimate the equation using a fixed-effect linear probability model. Results are comparable. For example, the NHI significantly increased the probability of having a CT scanner, radiation isotope diagnostic equipment, linear acceleration equipment, NMR tomography, and shock wave lithotripsy by 3%, 2.2%, 1.3%, 0.6%, and 3.9%, respectively.

radiation isotope diagnostic equipment by 23.6%, linear acceleration equipment by 1.9%, NMR tomography by 1.2%, and shock wave lithotripsy equipment by 3.5%. Consistent with Sloan et al. (1986), this article finds that the effect of third-party payment on technology adoption is substantial.

The NHI reform also had positive effects on the use of the five technologies. Estimated coefficients are statistically significant at the 1% level, except for the use of CT scanners. The estimated marginal effects (at the mean of the independent variables) show that NHI increased the use of CT scanners by 28 patients and of radiation isotope diagnostic equipment by 26 patients in private hospitals, 6% and 11% of pre-NHI use, respectively. In contrast, the estimated effects on use of linear acceleration equipment, NMR tomography, and shock wave lithotripsy equipment were each less than 1%.

Estimates using our second control group, private teaching hospitals, also suggest that NHI increased technology ownership, adoption, and use (lower portion of Table 3). Three of five estimates of the effect on technology ownership are statistically significant at the 1% level, as are four of five estimates of the effect on technology adoption and utilization.

B. *Robustness Tests*

The principal finding—that the probability of technology ownership and adoption and the use of technology by private hospitals increased in the years after 1995—is consistent with NHI having a positive impact on technology adoption and use. However, there are a number of alternative explanations that must be examined before concluding that NHI is the most likely explanation for these changes.

Two pieces of evidence support the hypothesis that the observed effects were due to the NHI reform.[15] First, because the most significant differences between treatment and control groups are hospital size and scope, the authors restrict the sample to hospitals with more than 100 beds. Making treatment and control groups more similar can eliminate spurious effects. Using the same specification as in Table 3, results reported in Table 4 also suggest that NHI increased the probability of technology ownership and the utilization of technology.[16] Marginal effects are much larger than the estimates in Table 3, suggesting that NHI has larger effects on technology ownership and utilization for large hospitals.

The second piece of evidence concerns the differential effect in markets characterized by varying levels of access to health care prior to NHI. In principle, one would expect that effects of NHI would be largest in markets where a larger share of the population was uninsured. Although the authors are unable to find data on the uninsured population by county or city in Taiwan, the fraction of the population not in the labor force can be used as an alternative indicator of coverage. This nonworker rate provides a good index of coverage because only the working population had insurance coverage prior to NHI.[17] Table 4 shows that in counties with a relatively high nonworker rate, the predicted probabilities of technology ownership and adoption all increased after the NHI reforms. Use of technologies also had positive responses to the NHI reform. Effects are comparable to effects in the full sample (Table 3).

C. *Other Explanatory Variables*

Other explanatory variables of interest for the probability of owning technology are shown in Table 5. Hospitals with more beds are more likely to own technologies (except for a CT scanner). These results are consistent with the findings of Sloan et al. (1986) and Cutler and McClellan (1996) and suggest the impact of scale economies on technology adoption. Hospitals with more medical staff are more likely to own the technologies, with coefficients statistically significant at the 1% level. More physicians in the hospital make the use of technology more probable and make ownership more profitable. However, no consistent results are found on the effects of the number of specialties in hospitals. One possible explanation is that hospitals with more diverse specialties may more easily find alternative treatment or diagnostic methods rather than relying on these technologies.

15. Only the results using public nonteaching hospitals as the control group are reported.

16. The authors are not able to estimate the probability of technology adoption due to the small sample size when the sample is constrained to large hospitals.

17. Using the Human Resource Utilization Survey, the authors calculated the average nonworker rates between 1993 and 1998 by county.

TABLE 4
Sensitivity Analysis

	CT Scanner	Radiation Isotope Diagnostic Equipment	Linear Acceleration Equipment	NMR Tomography	Shock Wave Lithotripsy Equipment
Sample: hospitals with more than 100 beds					
Technology ownership probability ($N=921$)					
Private * NHI	1.254	1.810[a]	2.167[a]	0.167	1.808[a]
	(1.013)	(0.605)	(0.601)	(0.575)	(0.376)
	[0.064]	[0.144]	[0.137]	[0.011]	[0.151]
Intensive use of technology ($N=921$)					
(Dependent variables/1000)					
Private * NHI	0.640[c]	11.432[a]	11.908[a]	1.295[a]	0.591[a]
	(0.372)	(3.633)	(4.085)	(0.310)	(0.110)
	[0.589]	[0.239]	[0.030]	[0.036]	[0.153]
Sample: hospitals located in areas with nonworker share of population greater than 45% prior to NHI reform					
Technology ownership probability ($N=2381$)					
Private * NHI	0.855[b]	1.372[a]	4.770	0.865	2.140[a]
	(0.434)	(0.390)	(8.918)	(0.642)	(0.428)
	[0.098]	[0.080]	[0.052]	[0.026]	[0.054]
Technology acquisition probability ($N=1904$)					
Private * NHI	0.574[c]	2.146[a]	1.911[a]	0.783[b]	1.086[a]
	(0.306)	(0.580)	(0.544)	(0.388)	(0.364)
	[0.061]	[0.056]	[0.161]	[0.054]	[0.032]
Intensive use of technology ($N=2381$)					
(Dependent variables/1000)					
Private * NHI	0.383	13.175[a]	12.465[b]	1.103[a]	1.003[a]
	(0.300)	(2.874)	(5.709)	(0.331)	(0.154)
	[0.078]	[0.047]	[0.001]	[0.0001]	[0.0005]

Notes: Standard errors are in parentheses. Marginal effects (at sample mean) are in brackets. Other explanatory variables include NHI dummy, a dummy for private hospital, three dummies for number of beds (0–30, 301–600, over 600), number of specialties, number of medical staff, Herfindahl index, percentage of hospitals in region with technology, and year dummies for 1994, 1995, 1997, and 1998. Control group public nonteaching hospitals.

[a]Statistically significant at the 1% level.

[b]Statistically significant at the 5% level.

[c]Statistically significant at the 10% level.

There is no theoretical consensus on the effect of competition on technology adoption. These estimates suggest that hospitals in more competitive markets are more likely to own these technologies.[18] All five coefficients are statistically significant at the 1% level. This result is consistent with the "arms race" argument that in a monopolistically competitive market, hospitals are more likely to engage in nonprice competition by improving quality of care or prestige. In addition, a larger percentage of hospitals in the market having the technology increases the probability of technology ownership, and the coefficients are statistically significant at the 1% level for three technologies. The positive coefficients suggest the importance of learning effects and informational externalities as well as nonprice competition in the market. Finally, the correlation coefficients of the individual-specific effects are statistically significant at the 1% level. The results imply that the data are consistent with the random-effects model.

Table 6 reports other variables of interest for technology utilization. Hospitals with more beds are more likely to use four of five technologies, and those with more medical staff are more likely to use all five technologies. The number of specialties has mixed effects on

18. Because the Herfindahl index increases with concentration, a negative coefficient implies that increases in competitive structure (i.e., decreases in the Herfindahl index) increase the probability of ownership.

TABLE 5
Random-Effect Panel Probit—Technology Ownership Probability

	CT Scanner	Radiation Isotope Diagnostic Equipment	Linear Acceleration Equipment Tomography	NMR Equipment	Shock Wave Lithotripsy
Hospital controls					
0–30 beds	−1.484[a]	−0.540[a]	—	—	—
	(0.210)	(0.204)	(—)	(—)	(—)
301–600 beds	−1.004[a]	−0.799[c]	1.769	1.528[b]	1.027[a]
	(0.273)	(0.433)	(1.223)	(0.688)	(0.328)
>600 beds	−2.914[b]	0.053	2.284[c]	2.993[a]	2.545[a]
	(1.258)	(0.515)	(1.270)	(1.032)	(0.667)
Number of medical staff (00)	4.726[a]	2.297[a]	1.976[a]	1.519[a]	2.464[a]
	(0.866)	(0.406)	(0.579)	(0.451)	(0.637)
Number of specialties (0)	2.639[a]	−0.812[a]	0.730	0.862[c]	2.692[a]
	(0.235)	(0.267)	(0.604)	(0.452)	(0.384)
Market structure					
Herfindahl index	−4.027[a]	−4.021[a]	−28.062[a]	−16.381[a]	−22.911[a]
	(0.936)	(1.070)	(9.084)	(2.860)	(2.746)
Percentage of hospitals with technology	3.229[a]	8.239[a]	16.088[b]	1.333	7.601[a]
	(0.635)	(0.896)	(7.339)	(3.219)	(2.157)
Rho	0.895[a]	0.812[a]	0.949[a]	0.953[a]	0.947[a]
	(0.010)	(0.033)	(0.029)	(0.015)	(0.011)
Log-likelihood	−817	−579	−187	−245	−371
Sample size	3666	3666	3666	3666	3666

Notes: Standard errors are in parentheses. Other explanatory variables include *PRI**NHI dummy, NHI dummy, a dummy for private hospital, and year dummies for 1994, 1995, 1997, and 1998. Control group is public nonteaching hospitals.

[a]Statistically significant at the 1% level.

[b]Statistically significant at the 5% level.

[c]Statistically significant at the 10% level.

the use of technologies. Market competition increases technology utilization, which suggests strong nonprice competition. To attract patients or enhance their prestige, hospitals may increase the use of technology as a signal of better quality of care.

Although the percentage of hospitals in a market having a technology increases the probability of owning that technology (Table 5), its effect on technology use is limited. This result provides a warning signal about the efficiency of resource allocation. Nonprice competition may induce hospitals in an area to inefficiently duplicate specialized equipment, with the result that each one operates at a volume below that at which the average cost per service would be minimized.

VI CONCLUSION

More generous health insurance coverage is likely to encourage hospitals to adopt, own and utilize expensive medical technology. Examining changes in technology adoption, ownership, and use after the 1995 introduction of NHI in Taiwan, this article finds that the probability of technology adoption and ownership and the use of technology increased more for private hospitals than for public nonteaching and public teaching hospitals. Although there are a number of potential explanations for these results, the hypothesis that these are effects of implementing NHI is the most compelling.

Except for the expansion to universal eligibility, the terms of coverage under NHI are not significantly different from those of the preexisting Labor Insurance. Nevertheless, costs of care are significantly greater under NHI. For example, NHI paid 17–33% more per physician visit and 19–33% more per inpatient day (Chiang, 1997). Because technology advancement has been thought to be one of the most important factors escalating health-care costs,

TABLE 6
Random-Effect Panel Tobit—Technology Utilization

	CT Scanner	Radiation Isotope Diagnostic Equipment	Linear Acceleration Equipment Tomography	NMR Equipment	Shock Wave Lithotripsy
Hospital controls					
0–30 beds	−2.170[a]	−2.963[c]	—	—	—
	(0.148)	(1.718)	(—)	(—)	(—)
301–600 beds	−0.625[a]	−1.479	4.972	1.391[a]	0.509[a]
	(0.142)	(3.265)	(4.525)	(0.372)	(0.082)
>600 beds	−0.823[a]	8.467[b]	3.695	1.893[a]	0.799[a]
	(0.153)	(3.336)	(4.531)	(0.453)	(0.112)
Number of medical staff (00)	3.791[a]	5.332[a]	11.405[a]	2.195[a]	0.152[a]
	(0.033)	(1.756)	(0.526)	(0.069)	(0.044)
Number of specialties (0)	0.967[a]	−3.003	0.499	−0.047	0.653[a]
	(0.083)	(1.916)	(2.594)	(0.219)	(0.069)
Market structure					
Herfindahl index	−0.666	−29.414[a]	−98.035[a]	−9.311[a]	−5.147[a]
	(0.373)	(8.504)	(14.284)	(0.903)	(0.393)
Percentage of hospitals with technology	0.042[c]	26.131[a]	20.351	−1.434	−0.300
	(0.265)	(7.222)	(13.282)	(0.993)	(0.393)
Standard deviation of residual error	1.129	9.295[a]	7.468[a]	1.012[a]	0.515[a]
	(0.009)	(0.193)	(0.496)	(0.042)	(0.012)
Standard deviation of random effect	2.249	11.843[a]	21.597[a]	2.450[a]	0.912[a]
	(0.053)	(1.709)	(2.177)	(0.141)	(0.046)
Log-likelihood	−2354	−1097	−473	−491	−612
Sample size	3666	3666	3666	3666	3666

Notes: Standard errors are in parentheses. Other explanatory variables include PRI * NHI dummy, NHI dummy, a dummy for private hospital, and year dummies for 1994, 1995, 1997, and 1998. Control group is public non-teaching hospitals.

[a]Statistically significant at the 1% level.

[b]Statistically significant at the 5% level.

[c]Statistically significant at the 10% level.

the stimulus to technology adoption provided by more comprehensive health insurance offers an explanation for at least part of the increase in cost per service after the NHI reform.

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